This Dissertation Committee for Zheng Li certifies that this is the approved version of the following dissertation:

A PROBABILISTIC AND ADAPTIVE APPROACH TO MODELING PERFORMANCE OF PAVEMENT INFRASTRUCTURE

Committee:

____

Zhanmin Zhang, Supervisor

____

Carl T. Haas

____

C. Michael Walton

____

Randy B. Machemehl

____

Benito Fernandez-Rodriguez

A PROBABILISTIC AND ADAPTIVE APPROACH TO MODELING PERFORMANCE OF PAVEMENT INFRASTRUCTURE

by

Zheng Li, B.Sc., M.Sc.

Dissertation

Presented to the Faculty of the Graduate School of

the University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

Doctor of Philosophy

The University of Texas at Austin

May, 2005

To my parents and husband for their unconditional love and support

Acknowledgements

I wish to express my sincere gratitude to my supervisor, Dr. Zhanmin Zhang for his guidance, understanding, and encouragement through my graduate studies. His technical and editorial advice was essential for this research. This dissertation would never have been possible without his guidance and valuable advice.

I also want to express my sincere appreciation to Dr. Benito Fernandez for his enlightening discussions, delightful conversations, and scholarly advice. I would also like to thank Dr. Carl T. Haas for his invaluable comments and friendly help. Many thanks also to Dr. Randy Machemehl and Dr. C. Michael Walton for their participation, patience, and suggestions. Dr. Jorge A. Prozzi is also appreciated for providing the AASHO Road Test data for conducting this research.

I am grateful to the current and former members of the Transportation Infrastructure and Information Systems Research Group: Ampol Karoonstoontawong, Siddhartha Sinha, Ivan Damnjanovic, Anju Pillai, Irfan Ahson, Pithon Vithauascricharoen, Zach Pipemeyer, and Micheal Flaming. I would also like to show my special gratitude to Loretta McFadden for her never failing willingness to assist and encourage. Special thanks also to Feng Wang, Feng Hong, Runhua Guo, Xiaokun Wang, Brenda B. Zhou, and Zhong Wang for their friendship and kind help.

Finally, I would like to thank my parents for their unconditional love and support. I would also like to express my deep appreciation and gratitude to my husband, Jianming Ma, for his compassionate love and encouragement.

A PROBABILISTIC AND ADAPTIVE APPROACH TO MODELING PERFORMANCE OF PAVEMENT INFRASTRUCTURE

Publication No.______________

Zheng Li, Ph.D.
The University of Texas at Austin, 2005

Supervisor: Zhanmin Zhang

Accurate prediction of pavement performance is critical to pavement management agencies. Reliable and accurate predictions of pavement infrastructure performance can save significant amounts of money for pavement infrastructure management agencies through better planning, maintenance, and rehabilitation activities. Pavement infrastructure deterioration is a dynamic, complicated, and stochastic process with its outcome as the aggregated impact from various factors such as traffic loading, environmental condition, structural capacities, and some unobserved factors. However, existing performance prediction models are still constrained by inadequate consideration of the dynamic and stochastic characteristics of pavement infrastructure deterioration.

The goal of this research is to develop a probabilistic and adaptive methodological framework that is capable of capturing the dynamic and stochastic nature of pavement deterioration processes. The ordered probit model and the sequential logit model as probabilistic models are proposed to directly predict the performance of pavements in terms of their condition states by relating the performance to the structural, traffic, and environmental variables. The proposed probabilistic models were pilot-tested with pavement performance data collected during the AASHO Road Test, yielding promising preliminary results. In addition, these models were further enhanced as mechanistic-empirical models by incorporating certain primary response variables of pavements as explanatory variables. The comparison results show that the proposed models yield better predictions than the previously developed models. Then, a structural state space model is proposed to characterize the dynamic nature of pavement deterioration. The structural model allows the prediction of pavement deterioration to be adaptively updated with new inspection data, taking advantage of a polynomial trend filter and the Kalman filter algorithm. The preliminary results from a simulation case study indicate that the adaptive algorithm is robust and responsive to structural deviations of the pavement deterioration process.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1 INTRODUCTION AND OBJECTIVE

Highway transportation systems are designed and built to transport goods and people safely, comfortably, and efficiently. Since the construction of the interstate highway system in the U. S. was completed in the early 1990s, the federal-aid highway program has experienced a significant transition from its original focus on building the highway system to preserving or improving the highway infrastructure (FHWA, 1999). With the continuously increasing traffic demand and the higher expectation of highway users in terms of comfort, convenience, safety, and security, the Federal Highway Administration (FHWA) has to provide a tremendous amount of money to maintain and expand the national transportation system. From 1992 to 1997, $155 billion was authorized by the Intermodal Surface Transportation Efficiency Act of 1991 (ISTEA) and invested in the national surface transportation systems to have a "transportation system that is economically efficient and environmentally sound."(ISTEA, 1991) Following the ISTEA, another $218 billion was funded by the Transportation Equity Action of 2000 for the 21st Century (TEA-21) from 1998 to 2003 (FHWA, 2002).

Although tremendous amounts of money have been spent on the highway system, highway agencies are still constrained by the availability of funds as well as the demand for funds spent on highway projects (FHWA, 1998). To maximize the benefits and minimize the overall costs of maintaining or preserving the highway transportation system, pavement management systems (PMSs) have been proposed and implemented to help highway agencies cost-effectively manage their pavements from planning, design, construction, and in-service evaluation, to maintenance and rehabilitation (M&R). At the network level, PMSs are used for identifying the optimum strategies of M&R planning or project prioritization based on the aggregate data, while corrective actions for individual pavement sections are recommended based on the detailed individual section data at the project level. The benefit of implementing PMSs has been proved by many state Departments of Transportation (DOTs). For example, by implementing its pavement management system, the Arizona Department of Transportation saved $14 million in its first year of implementation (fiscal year 1980-1981) and $100 million in the first four fiscal years (Golabi et al., 1982; Kulkarni, 1984).

The effectiveness of M&R planning or project prioritization in the PMSs depends on the accuracy of the predicted future performance and observed current condition of a pavement. If the deterioration models used by the highway agencies in determining the M&R policies cannot sufficiently represent the actual deterioration process, the planned M&R strategies might be far from optimal (Durango and Madanat, 2002). Therefore, performance measurement and deterioration models are essential components of the PMSs.

1.1 Background in Modeling Pavement Performance

In order to measure and model pavement performance, it is necessary to clearly define pavement performance. According to the American Association of State Highway Officials (AASHO), pavement performance is defined as the serviceability trend of the pavement over a design period of time, where serviceability indicates the ability of the pavement to serve the demand of the traffic in the existing condition (AASHO, 1962). In other words, pavement performance can be obtained by observing or predicting the serviceability of a pavement from its initial service time to the desired evaluation time. Usually, pavement condition can be evaluated according to four aspects or evaluation measurements: roughness, surface distress, structural capacity, and skid resistance. Various indices have been developed to measure pavement performance in terms of either these individual aspects or a combination of them (Zhang et al., 1993). For example, the functional performance index, such as the Present Serviceability Index (PSI) and the International Roughness Index (IRI), is normally used to characterize the ride quality of a pavement, whereas the structural performance index, such as the structural number (SN), is employed to quantify the structural capacity. In this dissertation, the discussions are focused on using the PSI as the performance measurement of pavement sections.

Theoretically, the deterioration process of a pavement is the result of various factors affecting the mechanistic characteristics of pavements, such as traffic, environment, material properties, and the degree of maintenance. At the same time, pavement performance is also impacted by other latent factors which are difficult to observe (Madanat et al., 1995). Therefore, the uncertain characteristics or randomness in pavement deterioration processes are often observed. Furthermore, uncertainty can also arise from the inspection errors and inability to model the true deterioration process (Madanat, 1993). In other words, pavement deterioration is a complicated stochastic process. In addition, the deterioration rate of pavement sections is not constant but varying with time, indicating it is a dynamic process.

In the past decades, researchers have developed various infrastructure deterioration models varying from simple linear regression models to complicated Markov Chain models by using empirical, mechanistic, or mechanistic-empirical approaches. However, these models are limited in two aspects. First, the traditional deterministic models are inadequate to model the uncertainties associated with pavement deterioration processes. Although various stochastic models, such as Markov Chain models, have been developed to capture the stochastic characteristics, these stochastic models suffer from such limitations as the assumption that pavement deterioration is a stationary process. Second, most of the traditional performance models do not consider pavement deterioration as a dynamic process. In other words, most of the previous performance models are static in nature. Moreover, these models focus on developing deterioration models based on historical data, where updating the developed models with new inspection data is generally neglected.

In order to address these two issues discussed in the previous section, further research should be conducted to develop a probabilistic and adaptive approach to characterizing the stochastic and dynamic nature associated with pavement deterioration processes.

1.2 Research Goal and Objectives

The goal of this research is to develop a probabilistic and adaptive framework for modeling the deterioration process of pavements. The proposed framework should be able to capture the stochastic and dynamic nature of pavement deterioration processes by relating pavement performance to its causal variables in a probabilistic manner, taking advantage of new inspection data to further improve the prediction accuracy.

To achieve this goal, the following objectives are expected to be accomplished under this research:

1) The first objective is to develop ***probabilistic performance models*** for predicting the performance of flexible pavements. The developed models should incorporate the impact of relevant factors such as the environment, structural capacity, and traffic loading. These models should be able to capture the stochastic nature of the deterioration process of flexible pavements by directly predicting the probability of each condition state. In

addition, the proposed models should be validated with a data set that is not used for calibrating these models.

2) The second objective is to take the impact of M&R into consideration using ***a mechanistic-empirical approach***. This mechanistic-empirical approach employs primary responses (stress or strain) of pavement sections and connects them with pavement performance through the regression analysis.

3) The third objective is to develop ***an adaptive method*** to update the developed models with the new inspection data. The adaptive method should be compatible with the proposed performance models in terms of integration. Several scenarios should be tested to evaluate the effectiveness and robustness of the adaptive method.

1.3 Research Contributions

This research will benefit pavement management agencies through the provision of an improved approach to pavement performance predictions. Contributions of this research include:

1) The development of a probabilistic and adaptive framework describing the stochastic and dynamic characteristics of pavement deterioration processes; the framework can be expanded to model the deterioration of other civil infrastructure systems;

2) The development, calibration, and validation of ordered probit models and sequential logit models, using the AASHO Road Test data, to predict the probabilities with pavement condition states, where the probabilities are related to causal variables;

3) The development of mechanistic-empirical models to extrapolate the models out of the range of the AASHO Road Test by incorporating the primary responses of pavement sections into explanatory variables; and

4) The development of an adaptive method to improve the prediction accuracy of the pavement performance by taking new inspection data into consideration, where a structural state space model is employed to identify any structural deviations from the original trend.

1.4 Dissertation Layout

This chapter briefly introduces the concepts of pavement management and pavement performance, as well as the goals and contributions of the dissertation.

Chapter 2 focuses on reviewing the literature of modeling the performance of transportation infrastructures. In this chapter, previous works are classified into different categories based on the nature of these models. For each category, the advantages and disadvantages are discussed and summarized.

The nature of the pavement deterioration process is discussed in Chapter 3, where more detailed information is provided to demonstrate the reasons underlying the stochastic and dynamic nature of pavement deterioration. This is followed by a description of the proposed framework which captures those characteristics and illustrates the whole research procedure.

Chapter 4 describes the methodologies of the proposed probabilistic performance models. First, this chapter discusses discrtization schemes of defining pavement condition states. Then, the theoretical background and the parameter estimation of the ordered probit model are given. Next, the sequential logit model is also described as a paralleled approach to the ordered probit model for capturing the stochastic nature of pavement deterioration. The procedure for estimating the parameters of the sequential logit model is discussed in this chapter.

In order to demonstrate the application of the proposed probabilistic models with real data, Chapter 5 presents a case study of implementing these probabilistic models with the AASHO Road Test data. The model specifications and validation results are presented first. Then, the mechanistic-empirical approach is taken to incorporate the primary response variables of pavements as part of the explanatory variables in order to extend the model specification beyond the testing conditions of the AASHO Road Test.

Chapter 6 compares the developed probabilistic models in Chapter 5 with the Markov Chain models and a duration model developed with the same data set. After presenting the theoretical background of developing the transition probability matrixes (TPMs) of Markov Chain models and the duration model, the comparison criteria are established. The comparison results show that the proposed probabilistic models are better than the duration model and the Markov Chain models in terms of their prediction accuracy and goodness-of-fit.

The theoretical background of the adaptive model is presented in Chapter 7. This chapter begins with the discussion of representing the pavement structural deviations by a polynomial function. Then, the transition and measurement equations are formulated. The modeling structure and estimation process using the Kalman Filter are also explained in this chapter.

Chapter 8 presents the application of the adaptive model proposed in Chapter 7 with simulated case. Three scenarios are designed to represent the possible phenomena in pavement deterioration processes. Then, the prediction results are given and discussed. This chapter concludes that the adaptive model is feasible and responsive to significant structural deviations.

Chapter 9 summarizes the research effort and presents the conclusions. Future works are also recommended in this chapter.

CHAPTER 2 LITERATURE REVIEW

This chapter briefly reviews the background of pavement performance models. The literature related to modeling pavement performance is classified into different categories based on their nature. The main characteristics of these models are also discussed in this chapter.

2.1 Background

The FHWA required the DOT of each state to develop their own PMSs to manage their transportation network by 1993 (Zhang et al., 1993). The reason for this requirement arose from the increasing deterioration rate of the developed transportation infrastructure network. Generally, a newly constructed pavement deteriorates very slowly in its first ten to fifteen years of the design life, then deteriorates very fast if timely maintenance is not applied. The accelerated deterioration required a 45 percent funding increase in the 1980s and 1990s (Paterson, 1987). On the other hand, the legislative bodies required highway agencies to be more efficient and accountable for spending taxpayers' money. As a set of tools and methods for effectively managing the transportation infrastructure, a PMS was developed to satisfy the requirements of not only the legislative bodies but also public agencies. In order to illustrate different levels of users, a hierarchical structure of the PMSs has been proposed in Figure 2.1 (Haas et al., 1994). The hierarchical structure consists of three levels. The first level is an administrative level at which the funds are allocated among different categories of the transportation infrastructure. At the network level, pavement management agencies determine the M&R strategies, identify the corresponding locations, and schedule the M&R activities. Based on the optimum prioritization results, they assign the funds to their transportation networks. The detailed M&R treatments are dealt with at the project level.

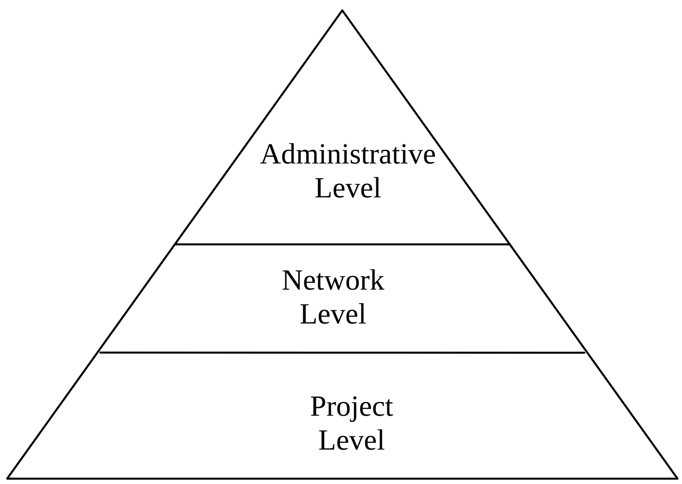

Figure 2.1 Hierarchical Structure of PMSs

Regardless at which level, the goal of a PMS is to help highway agencies provide high-quality and cost-effective service to highway users. A PMS includes three components (USDOT and FHWA, 1999):

- Data collection and management
- Analysis
- Feedback and update

Data and information play important roles in the system, because good management systems should be reliable built on information. The collected condition data can be used to evaluate the real-life performance of pavements, to predict the deterioration rate of the road network and the effectiveness of maintenance actions, and to further prioritize the projects cost-effectively based on the current state, projected trends, economic growth, and available resources. All these comprise the analytical core of the PMSs. After the implementation of M&R actions, monitoring the performance of the systems cannot be ignored in order to update the system analysis. The three components can be further extended to a generic pavement management process shown in Figure 2.2.

From Figure 2.2, it can be easily seen that performance modeling as an input to the decision-making process plays a vital role in a PMS. The quality of the performance models directly influences whether the optimal M&R strategies can be attained or not. In the past decades, a wide variety of pavement performance models have been developed to serve as the foundation of pavement management. Major characteristics of these models are discussed in the following sections.

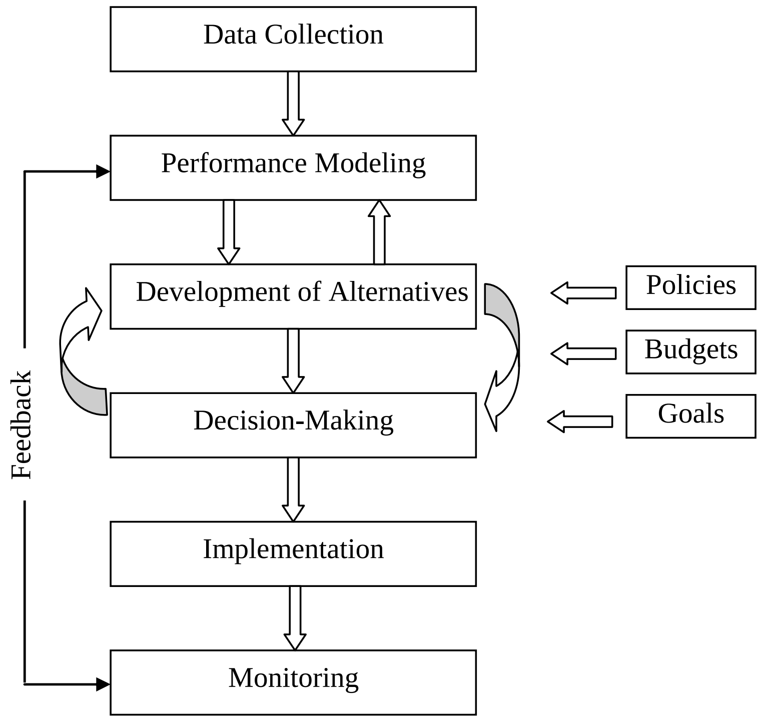

Figure 2.2 Generic Pavement Management Process (CSI, 2002)

2.2 Modeling Approaches of Pavement Performance Models

Based on modeling approaches, pavement deterioration models can be classified into three groups: mechanistic, empirical, and mechanistic-empirical. Historically, pavement behavior was studied using the mechanistic approach based on the physical principles such as the soil mechanistic theory, mechanical property of pavement materials under load, and multilayer structural analysis techniques. Most of these studies were conducted under limited experimental conditions. Therefore, they need to be validated and calibrated to the full range of real situations before implementing the developed mechanistic models. In addition, most of these models are still simple and only represent the material or structural responses in limited situations. Even though the mechanistic approach is regarded as the best to characterize the deterioration process, the development of reliable and acceptable mechanistic models is still at its early stage and requires a significant amount of time and effort for continuous studies.

The empirical approach employs statistical techniques to explain pavement deterioration with its explanatory variables. Although this approach has the capability to link the pavement performance with their causal variables, the explanatory variables taken are only based on their availability and statistic values. Consequently, this approach suffers from the limitations associated with the scope and range of the available data.

The mechanistic-empirical approach is the combination of the above two approaches. The mechanistic approach assists in determining pavement responses, structuring the explanatory variables and functional forms of empirical models. The final relationship between the response variables and pavement performance is developed with the statistical techniques adopted in the empirical approach. The coherent combination utilizes the advantages of both approaches and is expected to attain better performance models than the empirical approach only.

As a matter of fact, there is no absolute line between the mechanistic approach and the empirical approach, since all mechanistically based models involve elements of empiricism while empirical models also reflect some mechanistic principles. Consequently, the extrapolation capabilities of empirical models should not be underestimated; alternatively, the ability of the mechanistic models to extrapolate should not be overestimated (Nestorov et al., 1999). In practice, both empirical and mechanic models have been used in various developments and implementations of modeling pavement performance, although empirical and mechanistic-empirical approaches have been commonly used.

In most of the earlier studies, pavement performance models were developed with the empirical approach despite its limitations, including the pavement design method proposed by the American Association of State Highway and Transportation Officials (AASHTO) in 1993 (AASHTO, 1993). Currently, there is an increasing trend to develop mechanistic-empirical models such as the Guide for Mechanistic-Empirical Design of New and Rehabilitated Pavement Structures by the AASHTO Joint Task Force on Pavements and National Cooperative Highway Research Program (NCHRP) (TRB, 2005). In order to better summarize the previous work, a further classification of the literature is discussed as follows.

2.3 Deterministic Models vs. Probabilistic Models

Based on the prediction results of performance models, they can be classified as either deterministic or probabilistic. For the deterministic models, the future condition of a pavement section is predicted as the exact serviceability value or pavement condition index with the past information of the pavement. On the other hand, the probabilistic models predict the performance of a pavement by giving the probability with which the pavement would fall into a particular condition state, describing the possible pavement conditions of the random process (Durango, 2002).

Most of the pavement performance models developed in the early stages of pavement research are deterministic (Haas and Hudson, 1982). Currently, deterministic pavement performance models, such as the AASHTO regression performance model and various *S*-shaped curves, are still widely used. Based on the AASHO Road Test data, the initial pavement performance equation was developed to predict the loss of the serviceability by capturing the comprehensive effects of applied traffic loadings, material characteristics, and environmental conditions (AASHO, 1962). In order to accommodate the impact of the routine maintenance actions, the *S*-shaped curve which provides more accurate long-term prediction was proposed to reduce the deterioration rates at the end of pavement design period (Garcia-Aiaz and Riggians, 1984). However, such models are unable to effectively accommodate measurement errors and unobserved factors. As a consequence, the prediction error could go as high as 1 unit of the PSI value by using the AASHTO performance equation (Prozzi, 2001).

As part of the effort to improve such models, other regression models (Paterson, 1987; Prozzi, 2001) were proposed to consider more explanatory variables, such as pavement strength over different subgrades, environmental conditions, and maintenance actions, and different model structures based on the filed data. Paterson (Paterson, 1987) developed a number of incremental empirical model specifications at different levels of complexity to explain the real physical phenomena of pavement deterioration.

The concepts of the incremental models are illustrated in Figure 2.3. At time t_1, pavement condition is C_1 and the interest of engineers is to know the pavement condition C_2 at time t_2. The changes in pavement condition can be easily expressed in terms of a small period of time Δt, since they are normally used in managing and planning pavements. The time t can also be represented by the accumulated traffic. The reason for selecting the incremental or derivative type models is that these models do not require the original information of pavement condition and are developed based on the physical process of deterioration.

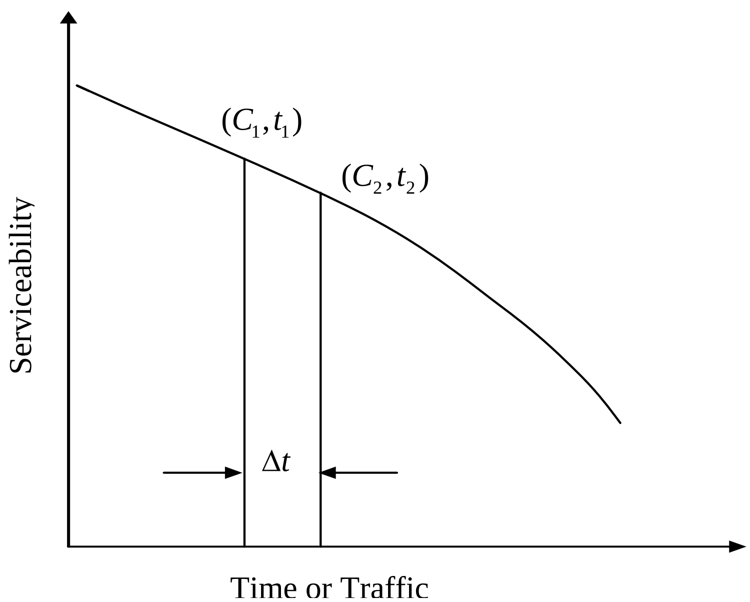

Figure 2.3 Illustration of Incremental Deterioration Models

Prozzi (Prozzi, 2001) has recently developed a mechanistic-empirical pavement performance model by using a two-step approach. An initial incremental nonlinear pavement performance model was developed based on the AASHO Road Test data by using the random-effects estimation methods. Then, with the integration of the joint estimation method, the bias of the parameter estimation in the prediction model was corrected by incorporating the in-service pavement data sets.

Although these models can provide good prediction results by considering the effects of the heterogeneity in the data sets or the maintenance activities, their deterministic prediction results are still used and hence they are not used to capture the inherent uncertainty in the process of pavement deterioration. In other words, despite the various efforts in improving the accuracy of deterministic models, these models are still constrained by the fact that they cannot effectively take the stochastic nature associated with pavement performance into consideration.

In the meanwhile, many probabilistic or stochastic models have been developed in order to characterize the uncertain characteristics of pavement deterioration processes. These previously developed probabilistic models can be summarized into three categories: econometric models, Markov Chain models, and reliability analysis. Each category covers a range of more specific applications. For example, Markov Chain models include homogeneous and non-homogeneous Markov Chain models. The details of the classification are illustrated in Figure 2.4.

In the last decade, econometric models were widely used to correlate the pavement distresses with their explanatory variables. Madanat et al. proposed a joint discrete-continuous model in 1995 to characterize the appearance of cracking and the propagation process of those cracks, where the binary logit model was used to determine whether the cracking appeared, and then a continuous model was developed to model the propagation process. The explanatory variables in the model include the structural number (SN) of the pavements, the thickness of the surface layer, and the number of wheel passes per unit strength of pavement (Madanat et al., 1995). Other econometric models were proposed to develop the Markov Chain models.

Another popular category of performance models is the Markov Chain. Golabi et al. proved the effectiveness of using the Markov Chain method in the 1980s by developing Markov Chain performance models in the state of Arizona (Golabi et al., 1982). In those Markov Chain models, the discretization of the continuous variable was undertaken based on different schemes because not much detailed information is needed at the network level of management (Madanat et al., 1995). Two types of Markov processes have been proposed according to different assumptions. The first is homogeneous Markov Chain process which assumes that the present condition state is only related to the previous state or the impact variables are constant during the analysis period (Golabi et al., 1983). In other words, the Markov Chain model has no memory of the entire past. On the other hand, the non-homogeneous Markov Chain models characterize the changes of the pavement deterioration rates over time. The Markov Chain models can be developed using the state-based or time-based models. The state-based models quantify the transition probabilities from one condition state to another in a predefined period of time, while the time-based models estimate the probability distributions of time it takes to change from one condition state to another (Mishalani et al., 2002).

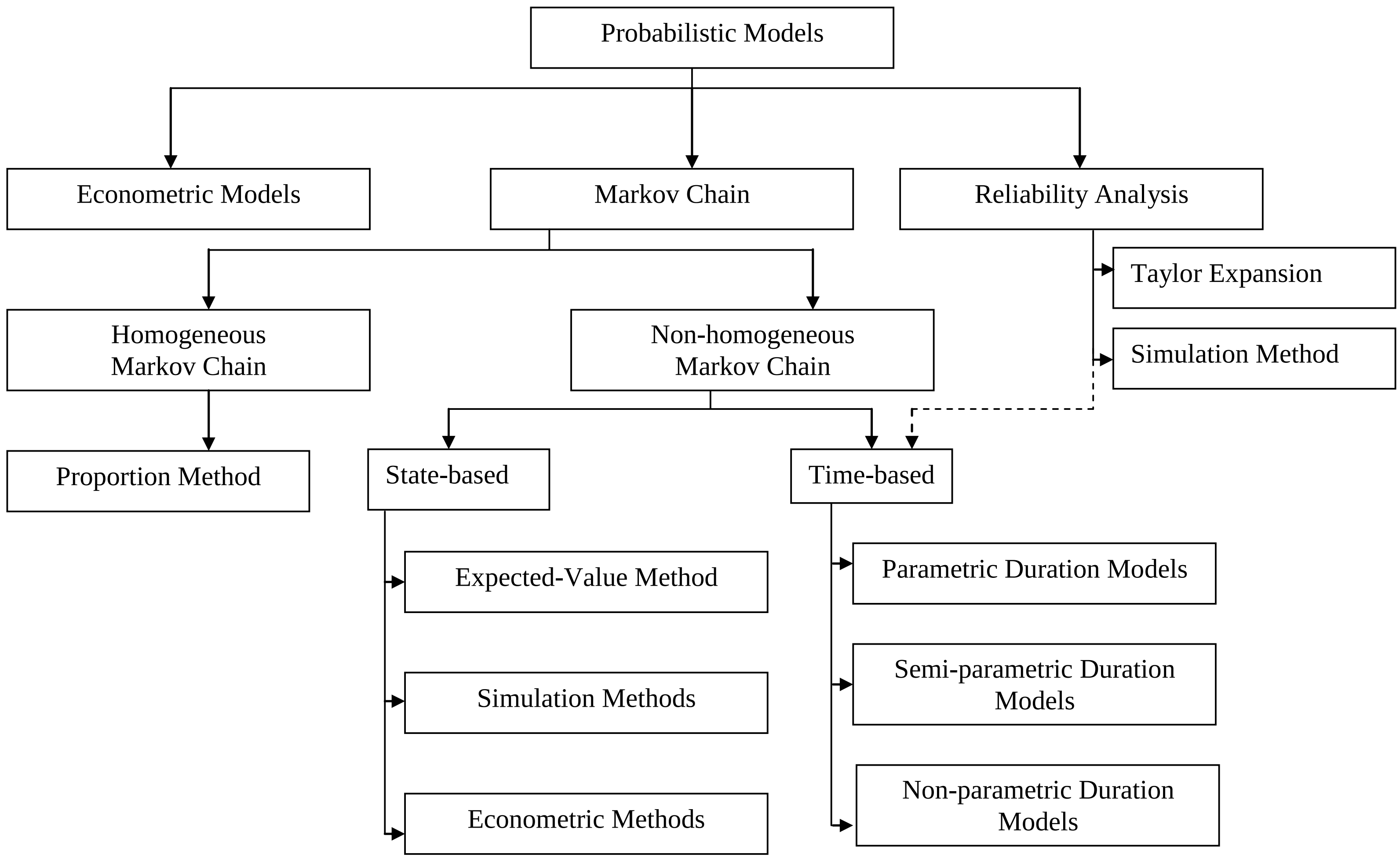

Figure 2.4 Classifications of Probabilistic Models

The state-based models are widely developed in practice, because they require less frequency of data collection. The core of the state-based Markov Chain models is the development of TPMs. Research methods, varying from the simplest proportion method (Wang et al., 1994) and the expected-value method (Jiang et al., 1987; Butt et al., 1987) to the complicated econometric techniques (Madanat, 1995), were used to develop the TPMs. The simplest approach used for developing a homogeneous Markov Chain model is a proportion method used by Wang et al. in 1994, which directly calculated the transition probabilities from one condition state to another (Wang et al., 1994). However, the prediction results of the homogeneous Markov Chain process are questionable, since the deterioration rate is not constant in the whole deterioration process (Butt et al., 1987). Therefore, non-homogeneous Markov Chain model is more proper to model this deterioration process.

The widely used non-homogeneous Markov Chain models were developed using the expected-value method in the 1980s. The expected-value method segments the pavements into different groups and then minimizes the differences between the expected values calculated using the TPMs and those obtained from the regression model with time as its explanatory variable (Jiang et al., 1987; Butt et al., 1987).

Another way of developing the state-based non-homogeneous Markov Chain model is the simulation approach which assumes design variables to follow different statistical distributions. The Monte Carlo simulation technique was used to produce the probability vectors representing the transition from one condition state to another, consisting of the TPMs. The calculated TPMs of pavement deterioration process determine the time-related non-homogeneous Markov Chain processes (Li et al., 1996). This simulation method can save a significant amount of money and effort compared with the previously discussed proportion and expected-value methods, because the collection of multi-year performance data is not required.

However, the above discussed methods cannot directly consider the impact of pavement types, environmental factors, traffic loading, and other relevant factors. The improved econometric methods such as ordered probit model, Poisson model, and random-effects probit models are proposed to connect the relevant explanatory variables to the transition probabilities (Madanat et al., 1995; Carnahan et al., 1987; Jiang et al., 1989; and Madanat et al., 1997). These models employed the statistical techniques to develop the relationship between the explanatory variables and dependent variables, providing more accurate prediction results than the previously discussed methods (Madanat et al., 1995). However, variables such as traffic and facility age could cause the TPMs to vary with time, resulting in the non-homogeneous facility deterioration process. Therefore, it is difficult to use these TPMs as the input to a stochastic Markov decision-making process, since most of the decision-making models are developed with the assumption that the deterioration process is stationary (Durango and Madanat, 2002).

The time-based models are considered as alternatives to develop the Markov Chain models. The time-based models focus on estimating the probability distributions of the time taken to transit from one condition state to another using the duration models (DeStefano and Grivas, 1998; Mauch and Madanat, 2001; and Mishalani and Madanat, 2002). Therefore, they also belong to the category of reliability models. These duration models can account for the censoring problems associated with data collection in the parameter estimation process. The hazard rate defined as a transition rate out of a certain state can be assumed to be a function of explanatory variables. Based on the assumption of the hazard rates, the duration models are further classified as: parametric duration models, semi-parametric duration models (Cox proportional hazard models), or nonparametric duration models. Most of parametric models assume that the hazard rates follow the Weibull distribution (Prozzi and Madanat, 2000; Vandem et al., 1997). They can characterize the nonlinear accumulated hazard rates. The estimated parameters of the Weibull distribution can be used to test whether the homogeneous Markov assumption is valid or not. But the Weilbull distribution assumption for the hazard rates in these parametric duration models is questionable because of the lack of explanations of the underlying assumption. Both Cox proportional hazard models and nonparametric models were proposed to theoretically solve the problems stemming from the predefined distributions for the baseline hazard (Mauch and Madanat, 2001; DeStefano and Grivas, 1998). Although the Cox proportion hazard model relaxes the parametric assumption of hazard specification and also considers the impact of the covariates, the baseline hazard cannot be estimated using a partial likelihood estimator (Cox, 1972). The nonparametric duration model is attractive because of its simplicity and accuracy in estimating hazard rates, but it cannot relate the dependent variable to the relevant explanatory variables. For the efficiency of the models, Meyer reported that the nonparametric estimation does not suffer from substantial loss of efficiency even for situations where parametric models are appropriate (Meyer, 1987). Therefore, it is recommended that the test of the nonparametric hazard baseline be performed before conducting any parametric analysis with duration data.

The time-based and state-based modeling methods are complementary in the sense that the state-duration probability density function used to calculate the transition probabilities can be estimated using a time-based model. The selection of the modeling approach primarily depends on the nature of the available data. The time-based model requires accurate observations of performance data spanning the whole deterioration period. If the measurements are not made frequently in short time windows, the measurement errors would result in the inaccurate time-based models (Mauch and Madanat, 2001). In reality, the data set satisfying these strict requirements is not easy to obtain. Therefore, these time-based models are not commonly used in practice.

To overcome the limitations associated with the previous models, one possible solution is to directly predict the pavement condition states by using a probabilistic approach. This approach can accommodate the stochastic characteristics of pavement performance and can also link the causal variables to pavement performance regardless whether the deterioration process is homogenous or not.

The third way of developing pavement performance model is based on reliability concepts. This method was widely used in the relative early time to determine the designed layer thickness of flexible pavements. Bourdeau considered the uncertainties and random factors in the pavement deterioration process by adopting the Shook and Finn design equation which is a function of two random variables (the expected traffic loads and the California Bearing Ratio (CBR)) (Bourdeau, 1990). A second-order, second moment function of the Shook and Finn design equation was developed based on the Taylor expansion for analyzing the reliability of the design equation. Another way of controlling the reliability is the simulation method which attracted the interest of many researchers. Easa et al. employed a Monte Carlo simulation method to calculate the joint probabilities of the low-temperature and thermal-fatigue cracking (Easa et al., 1996). Moavebzadeh controlled the designed thickness of pavements using primary responses which are influenced by variables with predefined statistical distributions. For example, the traffic load is assumed to follow the Poisson distribution (Moavenzadeh, 1976). George and Husain also proposed a simulation method to address the reliability of pavement thickness design (George and Husain, 1986). Although these simulation methods can achieve the goal of analyzing pavement design, they are time-consuming and cannot explain the pavement deterioration process explicitly. Other technologies such as the method of moments were implemented recently to analyze the reliability as an alternative approach to the Monte Carlo simulation method (Damnjanovic and Zhang, 2005).

2.4 Static Models vs. Dynamic Models

Performance models can also be summarized into static models and dynamic models. Typical examples of static models are regression models, in which the parameters of these regression models are estimated based on point estimations. In these regression models, measurement errors and unobserved factors are represented with an error term. The dependent variable of regression models relies only on explanatory variables. In this case, the research emphasis on regression modeling has traditionally been on the development of relationships between the explanatory variables and independent variable based on historical data. As a result, the changes in estimated values of the model parameters over time might be neglected, making the estimated regression model less reliable, especially when the deterioration process is dynamic.

Furthermore, updating developed regression models with new inspection data is frequently neglected. Although some researchers have used newly collected data to refine the estimation of their model parameters (Cheetham, 1998; Gharaibeh and Darter, 2002), these approaches taken have been generally to re-estimate the regression models by including the newly collected data in the original data set using the same point estimation procedure. The nature of parameter estimation prevents such adaptive methods from being effectively used for modeling a deterioration process with dynamic characteristics, since the present pavement condition is very important in the prediction process. To be more specific, the prior knowledge of pavement deterioration history may only contribute little to the prediction if the deterioration process is random. In addition, decision-makers in the highway agencies also pay more attention to the current pavement condition rather than the historical information (Carnahan, 1988).

Another approach for updating model parameters is Bayesian statistics which adjust beliefs based on the changing evidence in terms of uncertainty (Bernardo and Smith, 1994). The advantage of Bayesian statistics is that it does not require a significant amount of prior knowledge of the deterioration process. In addition, Bayesian statistics represent the certainty associated with the process with probabilities (West and Harrison, 1997). Given the advantages of the Bayesian statistics, researchers have applied Bayesian method to refine the parameters of infrastructure deterioration models in the last decade (Lu and Madanat, 1994; Hajek and Bradbury, 1996). Lu and Madanat refined the parameters of a bridge logistic model using the Bayesian approach, helping reduce the inherent uncertainty in the prediction (Lu and Madanat, 1994). Hajek and Bradbury incorporated the experts' opinion as the prior belief into the modeling process, and updated the prior model using the Bayesian statistical approach to improve the conventional performance models (Hajek and Bradbury, 1996). Durango and Madanat updated the weights for infrastructure deterioration rates by using Bayes' law to improve the representation of facility deterioration (Durango-Cohen and Madanat, 2002). Although earlier research studies have successfully addressed the issue in updating the parameters of the performance models, they are limited by the inadequate consideration of the dynamic and stochastic nature of the transportation deterioration process, especially when the inspection is conducted with short-time intervals or on a real-time basis with sensing technologies.

In contrast to the static models discussed above, a dynamic model is aimed at modeling a process which changes with the passage of time. Since knowledge of the infrastructure deterioration mechanism is incomplete, the process of infrastructure deterioration may not be predicted in an exact manner. These facts explained the difficulty of developing pure mechanistic models for the infrastructure deterioration process. As a matter of fact, even if the mechanistic approach can explain the physical laws of pavement infrastructure deterioration, inherent uncertainties within the deterioration process cannot be completely determined. The reason for this is that such uncertainties stem from uncontrollable and unpredictable disturbances (Maybeck and Peter, 1979). The development of dynamic models can help improve our understanding of the infrastructure deterioration process and further help management personnel in making better decisions (West and Harrison, 1997).

As a typical dynamic model, the Box and Jenkins time series model is widely used to characterize a dynamic process. Such time series models have been used to predict pavement cracking, roughness, and traffic properties (Lu, et al., 1992; Okutani and Stephanedes, 1984; Ashok and Ben-Akiva, 2000). Generally, one of the popularly used Box and Jenkins time series models is the autoregressive (AR) model. AR models are appropriate for predicting stationary processes with constant means and variances. However, AR models fail when the dynamic process experiences significant changes at critical time points, as these changes indicate that the process has deviated from its previous trend, fundamentally violating the stationary assumption of AR models. In order to improve traditional AR models, Lu et al. developed an adaptive algorithm with the ability to adjust its structure for capturing these deviations (Lu, et al., 1992). Although the developed algorithm can characterize the nonstationary property of the pavement deterioration process, the proposed algorithm is restricted by the requirement to determine the order of the adaptive processor and the parameters related to the length of the adjustment step. An inappropriate determination of these parameters would make the algorithm unstable or difficult to converge. Ashok and Ben-Akiva calibrated a 4^{th}-order AR model to predict the real-time origin and destination demand by using the Kalman Filter (Ashok and Ben-Akiva, 2000). Since the developed 4^{th}-order AR model was based only on the historical data of the dependent variable, the historic peculiarities might suggest totally inappropriate models. That is to say, mathematical expressions of these time series models are formulated without substantial foundation regarding the physics of the system except for observed data (West and Harrison, 1997). Thus, the reliability of such models is questionable to some degree. Even if these models include the explanatory variables, there is no guarantee of their accuracy. Furthermore, these time series models employed a transfer function to absorb trends and seasonal components as well as the noise component by appropriately differencing the data. To be more specific, differencing converts each element of a time series into its difference by subtracting from its k^{th} previous or after element (Box and Jenkins, 1976). This differencing results in highlighting the noise and perplexing a meaningful explanation for the time series models. Moreover, the differencing may not successfully remove the abrupt changes in a nonstationary process.

Pavement deterioration is a dynamic process where infrastructure performance is affected by the structural characteristics, environmental conditions, and traffic loadings. Therefore, a dynamic model is more appropriate than existing static regression models for predicting the conditions of transportation infrastructure. However, a pure time series model is essentially unreliable in that it statistically describes situations without explaining the physical principles of the process by linking independent variables to explanatory variables. On the other hand, regression models do not provide adequate consideration of measurement errors.

2.5 Summary

The literature review reveals that although numerous performance models are available for describing the pavement deterioration process, they suffer from the limitations of inadequately capturing the stochastic and dynamic nature of pavement deterioration process. In order to overcome the shortcomings of these models, a comprehensive and adaptive framework should be developed to characterize the stochastic and dynamic nature of pavement deterioration process.

CHAPTER 3 METHODOLOGICAL FRAMEWORK

The background of pavement performance models has been reviewed in Chapter 2. This chapter is devoted to identify and analyze the reasons causing the stochastic and dynamic nature of pavement deterioration. Furthermore, a methodological framework is proposed to capture such deterioration characteristics in order to overcome the shortcomings associated with previous models in this chapter.

3.1 Background

The performance of pavements can be evaluated from four aspects: skid resistance, surface distress, structural capacity, and roughness (Zhang et al., 1993). The skid resistance is defined as the developed force when a tire slides along the pavement surface to evaluate the safety which the pavement provides to users (Highway Research Board, 1972). If the skid resistance is inadequate, the accident rate attributed to the skid resistance increases. Surface distress includes “any indications of poor or unfavorable pavement performance or signs of impending failure; any unsatisfactory performance of a pavement short of failure” (HRB, 1970). Different types of surface distress of flexible pavements can be grouped into three categories: fracture, distortion, and disintegration. Surface distress is related to both roughness and structural integrity. Structural capacity is defined as the ability of a pavement to carry traffic loadings. The structural capacity of flexible pavements can be represented by the structural number of a pavement section. Roughness represents irregularities or unevenness of the pavement surface. The concept of roughness is often considered to be inversely proportional to the ride quality, indicating the level of comfort for road users and the smoothness of pavement surface. As an important evaluation aspect, roughness affects not only the ride quality but also vehicle operating costs, fuel consumption, and maintenance costs (UMTRI, 1998).

The pavement performance concept was initially developed during the AASHO Road Test (Carey and Irick, 1960). Since pavement performance is defined as the serviceability trend of a pavement over the designed period of time, the serviceability for each time point needs to be measured in order to achieve the trend. As a result, the present serviceability was proposed to represent the ability of a pavement to serve high-speed, high-volume, mixed traffic in its existing condition. To attain the present serviceability, the individual present serviceability, ranging from 0 representing the very poor condition to 5 representing the very good condition, was proposed to represent the individual rating of present serviceability of a pavement section. Individuals with different views and attitudes were chosen to form a panel representing road users. After the panel members were taught these serviceability concepts and basic rules, they were taken to the filed to make their own ratings about the ride quality of pavement sections. Figure 3.1 shows the form they used for evaluation. These individual present serviceability ratings were averaged to obtain the Present Serviceability Rating (PSR). In order to avoid the subjective nature of the PSR, the correlation between the PSR and the objective measurements of cracking, slop variances, rut depths, and patching were established to attain the PSI so that the subjective PSR could be predicted with the objective measurement of distress and roughness. Although the rut depth, cracking, and patching were included as some of physical measurements, the roughness was the most significant factor of the PSI prediction (AASHO, 1962).

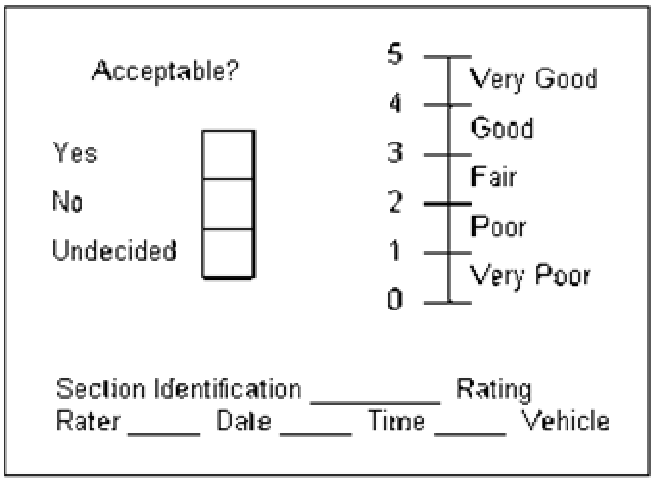

Figure 3.1 Individual Present Serviceability Rating Form (AASHO, 1962)

It should be pointed out that even though the performance-serviceability concept was developed during the AASHO Road Test, it still serves as the basic concept in the AASHTO pavement design method that is currently used by most of the state DOTs.

3.2 Probabilistic Concepts

In general, the deterioration process of pavements is a result of various factors affecting the mechanistic characteristics of the pavement, such as traffic, environment, construction, age, and the degree of maintenance. Indeed, these factors result in cracking, excessive deformation of pavements, and disintegration of pavement material. For example, the cracking of pavement is the result of excessive loading, fatigue, thermal changes, moisture damage, slippage, or contraction of materials. Because of its complexity, the deterioration process is associated with uncertainty and variability. How to capture the uncertainty and variability characteristics of pavement deterioration becomes a critical issue.

In order to model the uncertainty and variability, the underlying reason of the uncertainty and variability must be clearly understood. The variability refers to variations of pavement performance at different locations. The variation is related to the different materials, structural properties, traffic loadings, and climate (Sun, 2001). These variations can be analyzed using the statistical techniques. The uncertainties of pavement performance come from three aspects. The first aspect is the measurement errors which can cause a high degree of prediction uncertainty. These measurement errors are caused by technological limitations, data processing errors, environmental impacts, data interpretation errors, and other errors related to the nature of measurement. These errors interact with each other leading to the measurement bias and random errors. Even though some measurement biases can be removed by calibrating measuring equipment, analyzing correlation, or analyzing variance or covariance, the random errors cannot be corrected but characterized using the statistical techniques (Humplick, 1992). The second aspect of the uncertainty is the inherent randomness of pavement deterioration processes. The inherent randomness has been observed in the AASHO Road Test by measuring the performance of two identical pavement sections after applying the same traffic loading. The experimental results indicate that even two identical pavement sections had different performance trends, given the identical traffic loadings and environmental conditions. The third aspect is the inability to model the true deterioration process, because pavement performance is also impacted by other latent factors which are difficult to observe. Such uncertainty can be quantified by using the standard errors of predictions calculated by the performance models (Madanat, 1993).

In order to capture the uncertainty and variability associated with pavement deterioration, abundant research has been conducted. As discussed in Chapter 2, the performance models can be classified into deterministic models and probabilistic models. For the deterministic models, the prediction results are single numbers of pavement performance. Most regression models are considered as deterministic, although the regression models are comprised of a deterministic relationship and a disturbance term. The reason is that the disturbance term in the regression models are not used in practice.

Figure 3.2 illustrates the conceptual prediction results from the deterministic models and probabilistic models. The solid line indicates the deterministic prediction results calculated only using the deterministic relationship which explains the observed phenomena. However, pavement deterioration is not a deterministic process. The deterministic prediction cannot avoid causing the prediction errors because the deterministic relationship cannot fully explain the influence of every factor on pavement performance. If the disturbance term of the regression models is used in the prediction process, the predicted results are associated with certain confidence intervals. Since the disturbances are normally assumed to follow a normal distribution with zero mean and constant variances, the prediction results of the regression models also follow certain distributions. Therefore, the solid line in Figure 3.2 illustrates the expected prediction results of the regression models. If the actual pavement conditions are also distributed normally, they are distributed symmetrically about the expected prediction results shown as a bell curve in Figure 3.2. In this sense, the probability of pavement conditions falling into a certain confidence interval can be easily calculated. As a popular probabilistic method of modeling performance, Markov Chain methods discretize the pavement condition index into different states and then calculate the probability of falling into each condition state. In Figure 3.2, the five dashed lines represent the boundaries of the five condition states. Developing accurate TPMs is a difficult task that requires a significant amount of data, time, and effort. Furthermore, the developed Markov Chain models based on the non-homogeneous assumptions may complicate the Markov decision-making process and even make it difficult to solve.

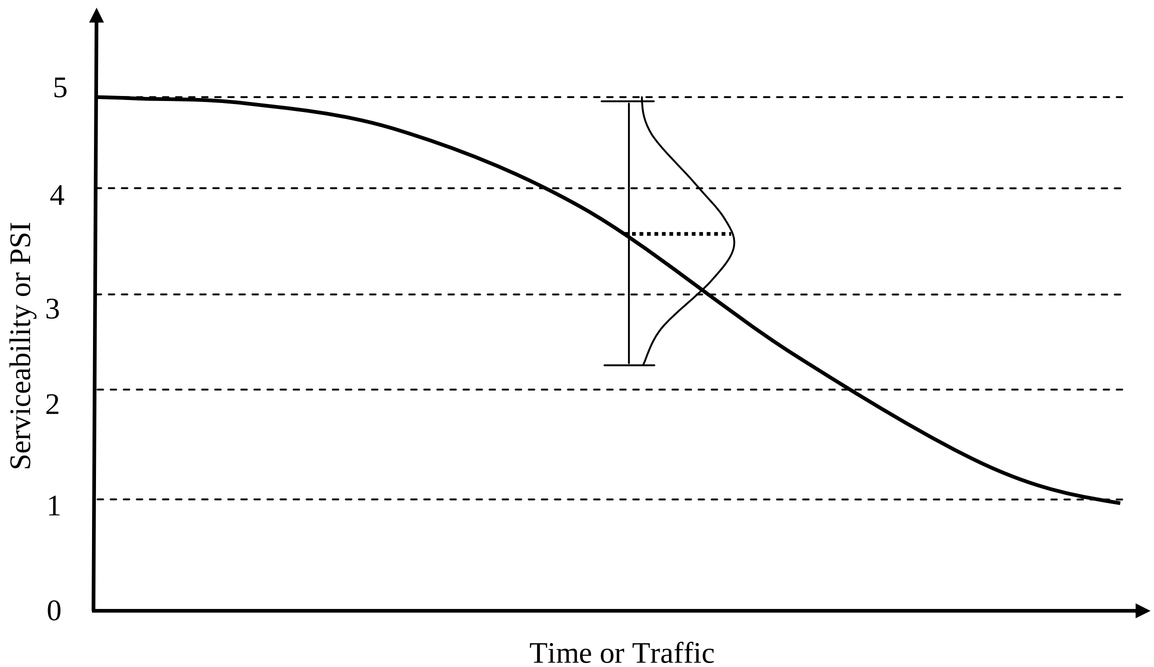

Figure 3.2 Illustrations of Deterministic Models and Probabilistic Models

To overcome the limitations associated with these previous models, a possible solution is to directly predict the pavement condition states using a probabilistic approach. The modeling process can be illustrated in Figure 3.3. This approach can accommodate the stochastic characteristics of pavement performance and can also link the causal variables to pavement performance.

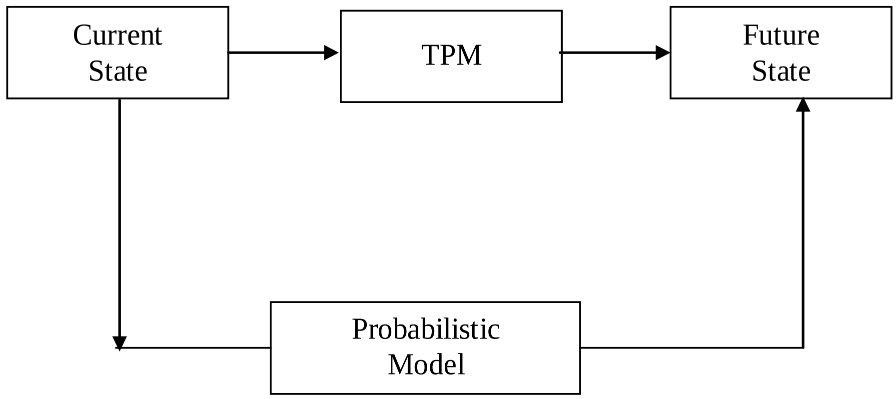

Figure 3.3 Illustration of the Proposed Probabilistic Model

3.3 Dynamic Concepts

Pavement conditions change over time as the result of observed relevant factors and unobserved disturbances. Therefore, the pavement deterioration process is a dynamic process. In previous studies, the static performance models are developed based on the available data. For example, a prediction conducted using the regression is illustrated in Figure 3.4. The dashed line labeled A represents the expected pavement conditions over time. The vertical lines with upper and lower bars represent the confidence intervals of prediction which increases with the time. The actual deterioration process is represented with a solid line labeled B. It appears that the pavement performance model overestimates the pavement performance. The overestimation would lead to insufficient M&R actions, since the prediction results of performance models are the input to decision-making of M&R treatments (Durango, 2002).

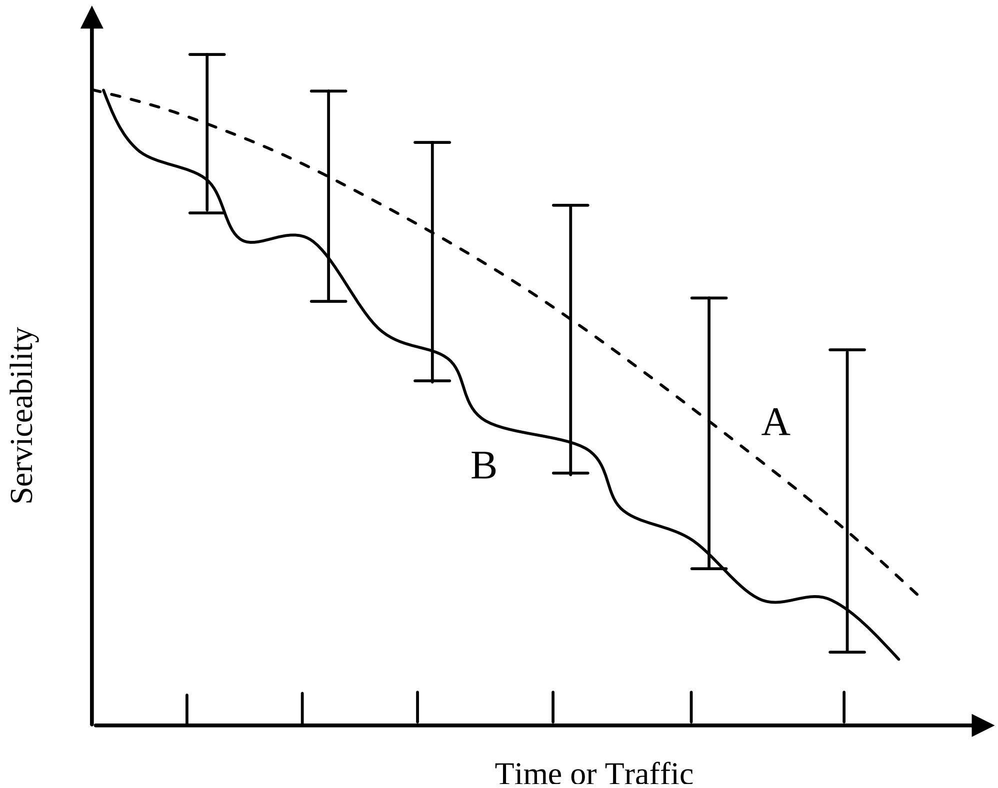

Figure 3.4 Predicted and Actual Deterioration Process

This overestimation is related to three issues. First, since the knowledge of the mechanism of pavement deterioration is incomplete, the properties exhibited by the process may change in an unpredicted manner. Although engineers have developed various mathematical models to represent this deterioration process, no mathematical models can be considered perfect since such models can only explain some aspects of the deterioration process interested by engineers. Second, even if mathematical models can provide the physical structure of the pavement deterioration process, parameters of the mathematical models cannot be determined absolutely because of uncertain and time-varying properties associated with the process. This time-varying characteristic stems from the varying relevant factors such as traffic and environment, whose values change over time and are impacted by unknown disturbances (Ljung and Soderstrom, 1983). Third, obtaining information which includes all possible relevant variables impacting the deterioration process is difficult, because of the limitations in measurement technologies and the lack of knowledge, causing most of the available data incomplete or noise-corrupted. As a result, the quality of pavement performance models cannot be controlled without properly dealing with the noise and incompleteness of the available data (Maybeck and Peter, 1979). In order to deal with the time-varying parameters of the mathematical models and incompleteness of the available data, a dynamic modeling approach should be used to express and model the behavior of the pavement section over time.

The most important aspect of the dynamic models to be dealt with is time-varying parameters. In some cases, the model parameters or even model structures change with time, which makes the defined model structures or parameters appropriate only locally or in a certain period of time. Therefore, it is necessary to update the corresponding parameters over time when new observed data are available (West and Harrison, 1997). The updating of the model parameters is critical, since most of PMSs determine their M&R actions mostly based on the most currently observed and predicted pavement conditions (Carnahan, 1988). Figure 3.5 illustrates the difference between the static and dynamic models. The solid line indicates an original performance model which is obtained from some historical data or experts' opinions. When the new data are available up to time t_1, it is easy to notice that the real trend of pavement deterioration indicates better performance than the predicted. In order to correct the underestimation of pavement performance, the model parameters need to be updated to minimize the prediction errors. Similarly, when the observed data from time t_1 to time t_2 are available, the updated trend signified by the dotted line cannot effectively represent the pavement deterioration trend. Therefore, the dotted trend needs to be adjusted to achieve better prediction results.

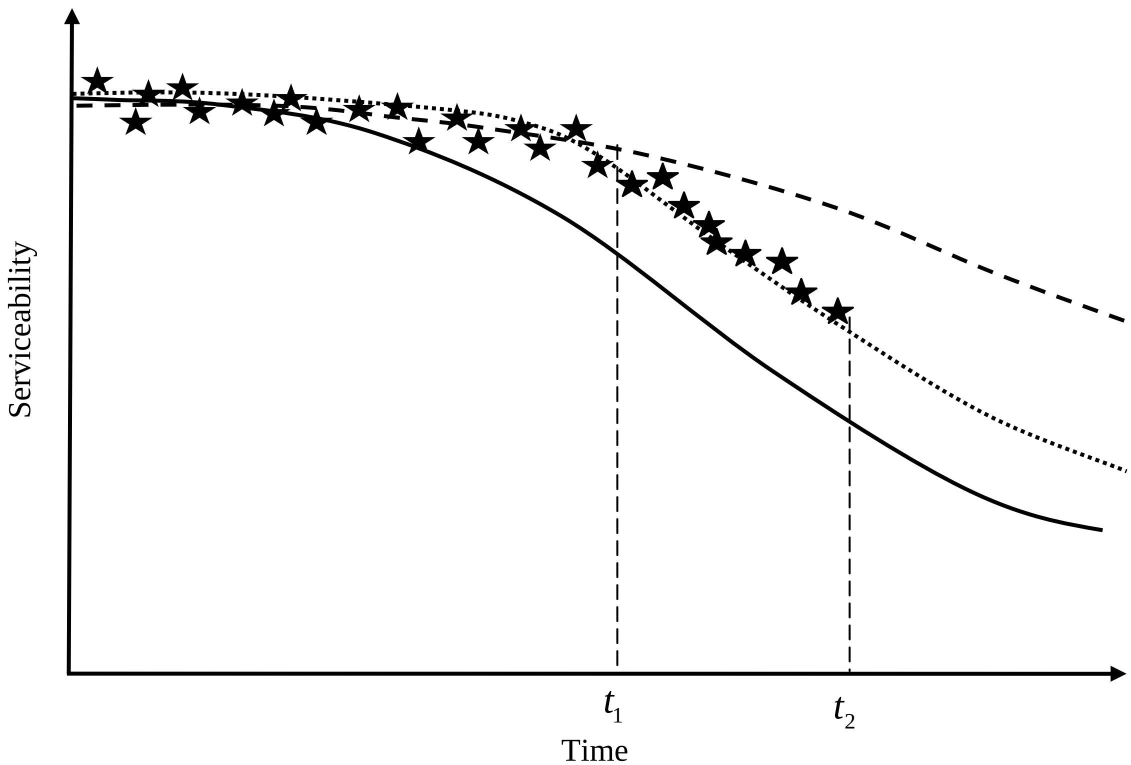

Figure 3.5 Illustrations of Static Models and Dynamic Models

Bayesian statistics and time series models have been used to model the dynamic deterioration process. The core of these approaches is a batch or recursive parameter estimation process designed to minimize prediction errors using algorithms by searching for optimal estimates of past, present, and even future states. The batch parameter estimation process, also called offline estimation, separates the data collection and parameter estimation, while the recursive process as the online estimation infers the parameter estimation at the same time as the data collection (Ljung and Soderstrom, 1983). These recursive parameter updating methods require less data storage space than the classical batch estimation methods; and the performance of dynamic models is improved through this recursive updating process.

Since the regression models are estimated based on the point estimation, no dynamic characteristics are reflected. The time series models generally describe situations statistically, without relating them to explanatory variables. Historic peculiarities are likely to suggest totally inappropriate models (West and Harrison, 1997). In addition, previous researchers did not conduct adequate studies on incorporating new inspected data into the modeling process to improve the performance models. Therefore, a comprehensive and adaptive methodology is proposed to characterize the dynamic nature of the pavement deterioration process. The proposed methodology is responsive to dynamic changes and can be easily integrated with the previously developed performance models.

3.4 Development of a Research Framework

In order to capture the stochastic and dynamic characteristics of pavement deterioration, probabilistic models and structural state space models are proposed. The overall framework of this research is presented in Figure 3.6.

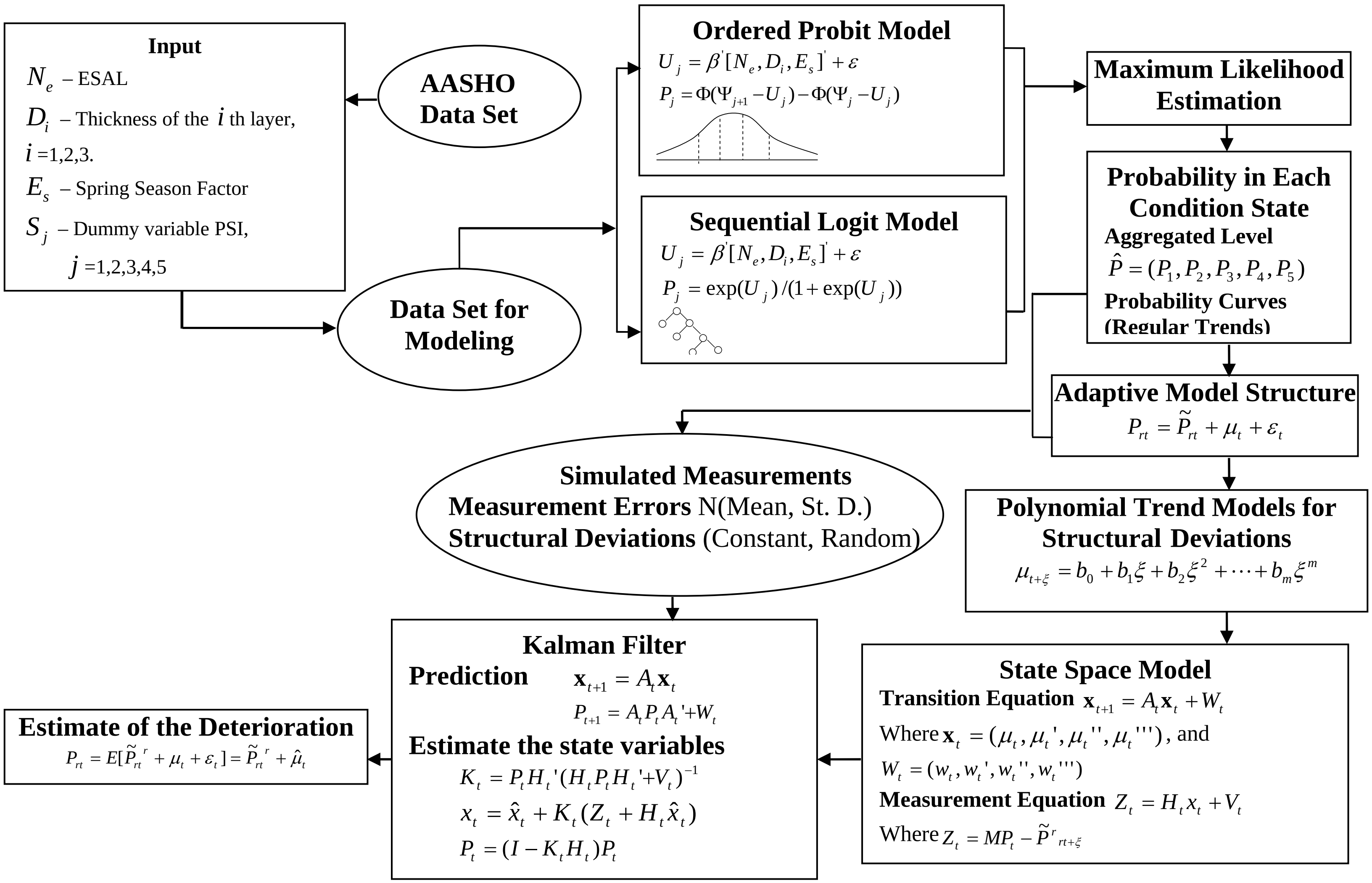

Figure 3.6 Major Components of the Methodological Framework

First, the AASHO Road Test data set to be used for the research is identified. Second, observations of flexible pavements are extracted from the AASHO Road Test data set; the variables which affect the flexible pavement performance are recognized and defined. Third, the ordered probit model is proposed in order to capture the stochastic nature of pavement deterioration. The model specifications are estimated through the maximum likelihood estimation method based on 80 percent of the data set used for modeling, while validation of the estimated model specifications is conducted using the remaining 20 percent of the data. Fourth, the sequential logit model is formulated, estimated and validated using the same data sets. Fifth, an adaptive structural state space model approach is proposed to include the regular condition curve calculated from the ordered probit model, the structural deviations from the regular condition curve, and random fluctuation. Sixth, the polynomial trend model as the core of the adaptive model is developed to model the structural deviations. Seventh, a state space model is formulated based on the polynomial trend models. Eighth, the state space model is recursively estimated by the Kalman Filter algorithm with the simulated data based on the prior estimated original trend and the adaptive model structure. The performance of pavements can be predicted using the adaptively estimated structural state space model.

3.5 Summary

This chapter has presented the reasons causing the probabilistic and dynamic nature of pavement deterioration and proposed a comprehensive methodological framework to characterize such characteristics. Under this framework, the key components are the development of the ordered probit model, the sequential logit model, and the adaptive algorithm. The details of these components are discussed in the following chapters.

CHAPTER 4 METHODOLOGIES OF PROBABILISTIC MODELS

In order to capture the probabilistic and dynamic nature of pavement deterioration, a comprehensive methodological framework has been proposed in Chapter 3, where mathematic models are integrated into the framework coherently. In this chapter, the theoretical background for the two models, the ordered probit model and the sequential logit model, are discussed in detail.

4.1 Establishment of Pavement Condition States

As defined in Chapter 2, probabilistic models are developed to calculate the probabilities with which a pavement deteriorates into its condition states. Therefore, the definition of pavement condition states is essential for probabilistic models. Pavement condition states can be defined from either discrete measurements or continuous measurements. The discrete measurements represent the relative ratings of measured pavement conditions using a scale from 0 to k (Madanat et al., 1995). In this case, the condition states can be easily established corresponding to the scale itself. For the continuous measurements of pavement conditions, the condition states can be established by discretizing continuous condition ratings, such as the Pavement Condition Index (PCI) or PSI, based on a selected discretizing scheme. To be more specific, the discretization is to divide the continuous condition ratings into intervals which correspond to different condition states. For example, the PCI ranging from 0 to 100 was evenly discretized into 10 condition states illustrated in Table 4.1 (Butt et al., 1987). The discretization of such a continuous pavement condition index is because the discrete condition states of the pavements are commonly used for planning M&R activities at the network level (Golabi et al., 1982). Through this discretization process, the calculation complexity of planning M&R strategies can be reduced.

Table 4.1 Pavement Condition State Classification (Butt et al., 1987)

PCI Range	Condition State	State Classification
91-100	10	Excellent
81-90	9	.
71-80	8	.
61-70	7	.
51-60	6	.
41-50	5	.
31-40	4	.
21-30	3	.
10-20	2	.
0-11	1	Failed

Since both the ordered probit model and the sequential logit model are employed to characterize the probabilistic process of pavement deterioration under the developed framework, pavement condition states must be established in order for the models to represent pavement condition probabilistically. Based on the discretization strategies discussed in the previous paragraph, the pavement condition indicator can be any one the engineers are interested to use. Let C_n represent the pavement condition state for pavement section n, where C_n can be any condition state from 0 to K. 0 represents the excellent pavement condition state, while K represents the failed pavement condition state. Once the condition states are established, the methodologies of the probabilistic models can be described.

4.2 Methodology Based on the Ordered Probit Model

The ordered probit model is widely used in the social sciences to model unobserved characteristics of each individual. The ordered probit model is based on the hypothesis that a single continuous variable exists and can be used to capture the latent propensity of the individual's choice (Mekelvery and Zavoina, 1975). Using the same hypothesis, the ordered probit model in this dissertation is employed to construct a discrete pavement performance model in which the observed pavement condition state is assumed to be related to the latent pavement performance propensity. The discrete performance model predicts pavement condition states as a function of traffic loading, environmental conditions, and structural factors.

4.2.1 Description of the Model Structure

Let C_n as the dependent variable represent the pavement condition state for pavement section n and an underlying response variable U_n be a measure of the latent deterioration propensity for pavement section n. U_n is assumed as a continuous variable varying from $-\infty$ to $+\infty$. The observed pavement condition state k is a reflection of the latent variable. U_n is specified to be a summation of a deterministic function of explanatory variables. In this case, the structure of the ordered-response model can be described as:

$$U_n = \beta^{'} X_n + \varepsilon_n \quad (n = 1, 2, \cdots, N) \tag{4.1}$$

where U_n is the underlying response variable;

X_n is a set of explanatory variables;

β is the estimated parameter; and

ε_n is the error term.

The above equation cannot be directly estimated, since U_n is not observable. But the observable state k that pavement section n falls in can be used to estimate the parameters in the model.

As such, C_n is governed by Ψ_k, the threshold values of the underlying response variable U_n. If the latent variable falls between the thresholds Ψ_k and Ψ_{k-1}, then the C_n falls into the corresponding state k. In this regard, the thresholds separate the continuous underlying response variable U_n into different states. That is:

$$C_n = k, \quad \textit{if and only if } \Psi_{k-1} < U_n \le \Psi_k \quad (k = 0, 1, \cdots, K) \tag{4.2}$$

If Equation 4.1 is substituted into Equation 4.2, then

$$C_n = k, \quad if \ and \ only \ if \ \Psi_{k-1} - \beta^{'} X < \varepsilon_n \leq \Psi_k - \beta^{'} X \tag{4.3}$$

Since the underlying response variable U_n is estimated, ε_n is assumed to follow a standard normal distribution with the mean 0 and the standard deviation 1. Then C_{nk} is defined as:

$$C_{nk} = 1 \quad if \ U_n \ falls \ in \ state \ k, \text{ for } (n = 1,2,\cdots,N) \text{ and } (k = 0,1,\cdots,K) \tag{4.4}$$

$$C_{nk} = 0 \quad otherwise, \text{ for } (n = 1,2,\cdots,N) \text{ and } (k = 0,1,\cdots,K) \tag{4.5}$$

The probability for pavement section n to be in the condition state k can be obtained by calculating the area of the probability density function of the latent variable U_n between Ψ_k and Ψ_{k+1}.

$$P(C_{nk} = 1) = \Phi(\Psi_k - \beta^{'} X_n) - \Phi(\Psi_{k-1} - \beta^{'} X_n) \tag{4.6}$$

where Φ is the standard normal cumulative distribution.

4.2.2 Maximum Likelihood Parameter Estimation of the Model

Based on the above equations, the maximum likelihood estimation procedure is used to estimate the parameter β and threshold Ψ_k. The likelihood function is

$$L = \prod_{n=1}^{N} \prod_{k=1}^{K} [\Phi(\Psi_k - \beta^{'} X_n) - \Phi(\Psi_{k-1} - \beta^{'} X_n)]^{C_{nk}} \tag{4.7}$$

In order to facilitate the calculation process, the logarithm is used to transform the likelihood function into a linear form. Thus, the log-likelihood function can be expressed as:

$$L^* = \log L = \sum_{n=1}^{N} \sum_{k=1}^{K} C_{nk} \log[\Phi(\Psi_k - \beta' X_n) - \Phi(\Psi_{k-1} - \beta' X_n)] \tag{4.8}$$

The unknown parameters can be estimated by maximizing the log-likelihood function subject to the constraint $0 \le \Psi_1 \le \Psi_2 \le \cdots \le \Psi_{K-1}$. To obtain the estimates of the unknown parameters, the partial derivatives of Equation 4.8 are taken with respect to the unknown parameters. Then, the partial derivatives of the log-likelihood function are set to zero and solved for the unknown parameters. Once the parameter β and the threshold Ψ_k are estimated, the probability for the pavement to be in each state can be obtained by calculating the areas under the normal distribution curve as illustrated in Figure 4.2. The shaded area in Figure 4.2 represents the probability of the pavement fall into pavement condition state k.

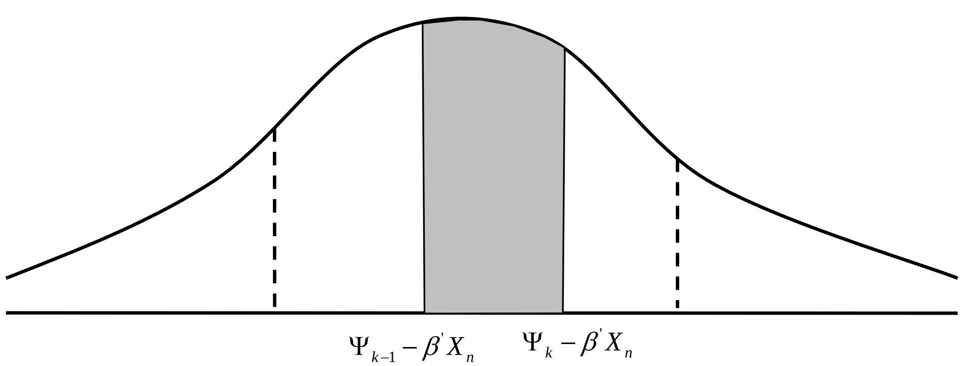

Figure 4.2 Probabilities of the Ordered Probit Model in Each Condition State

The mathematic formulation is shown in the following equations:

$$P(C_n = 0) = \Phi(-\beta' X_n) \tag{4.9}$$

$$P(C_n = 1) = \Phi(\Psi_1 - \beta' X_n) - \Phi(-\beta' X_n) \tag{4.10}$$

$$P(C_n = 2) = \Phi(\Psi_2 - \beta' X_n) - \Phi(\Psi_1 - \beta' X_n) \tag{4.11}$$

……

$$P(C_n = K) = 1 - \Phi(\Psi_{K-1} - \beta' X_n) \tag{4.12}$$

4.2.3 Goodness-of-Fit of the Model

In order to evaluate the developed model, three criteria are used to evaluate the goodness-of-fit of the model. A standard measure of fit for the estimation sample is the adjusted likelihood ratio index $\bar{\rho}^2$ value (Windmeijer, 1995), defined as:

$$\bar{\rho}^2 = 1 - \frac{L(\hat{\beta}) - M}{L(C)} \tag{4.13}$$

where $L(\hat{\beta})$ is the log-likelihood function value at convergence;

$L(C)$ is the log-likelihood function value at sample percentages; and

M is the number of the parameters including the thresholds estimated in the model.

The $\bar{\rho}^2$, analogous to adjusted R^2 indicating how well the model explains the available data, lies between zero and one. Theoretically, the greater the $\bar{\rho}^2$, the better the model fits the estimation data. However, studies have indicated that the $\bar{\rho}^2$ value usually is not high (Daganzo, 1982). The reason is that it is almost impossible to obtain a perfect model since the log-likelihood function is substantially different from zero in most cases. Furthermore, the $\bar{\rho}^2$ cannot be treated as the same as the adjusted R^2 which was defined by analyzing the residuals and testing correctness of models. In other words, the $\bar{\rho}^2$ is just an indicator of the fitness to data other than the model correctness. As a result, the adjusted log-likelihood index is commonly used for comparing different model specifications, although it is called the indicator of the goodness-of-fit.

In addition, the model can be also verified using the validation data set. At the aggregate level, the root mean square error (RMSE) which was derived from the average state probability proposed by Daganzo can be employed to compare the average predicted and actual percentages at each condition state (Daganzo, 1979). At the disaggregate level, the average-percentage-of-correct-prediction can be used as another criterion to evaluate the developed model. The average-percentage-of-correct-prediction is based on the maximum utility assumption that the condition state with the highest probability is set as the pavement condition state. The value of the average-percentage-of-correct-prediction lies between zero and one. Generally, it is assumed that the larger the percentage, the higher probability the model can provide the accurate prediction. The average-percentage-of-correct-prediction is calculated by using the following formula (Bhat and Pulugurta, 1998):

$$\overline{P} = N^{-1} \sum_{n} \sum_{k} \delta_{nk} \hat{P}_{nk} \tag{4.14}$$

where $\overline{P}$ is the average-percentage-of-correct-prediction;

N is the number of observations in the validation data set;

δ_{nk} is a dummy variable signifying whether pavement section n fall in state k;

and

$\hat{P}_{nk}$ is the predicted probability of pavement section n deteriorating to state k.

Although Equation 4.14 is not based on its original definition, the calculation results of Equation 4.14 coincide with those of its original definition (Horowitz, 1982). Therefore, Equation 4.14 is usually used to calculate the average-percentage-of-correct-prediction for simplicity.

4.3 Methodology Based on the Sequential Logit Model

Besides the ordered probit model, the sequential logit model is another approach to probabilistically predict the pavement deterioration process. The sequential logit method is usually used to depict the multi-response behavior with a sequential process in the social fields, such as predicting automobile ownership (Chu, 2002), determining employment stability (Kahn and Morimune, 1979), and analyzing automobile demand (Cragg and Uhler, 1970). This approach assumes that pavements would deteriorate in a sequential series instead of order. The ordered assumption makes the condition state into which pavements deteriorate to be determined by the successive partition of the real line, whereas the sequential assumption determines the condition state through a series of independent binary response models in which a pavement section deteriorates to the condition state with a higher utility (Bhat and Pulugurta, 1998). Another difference between the ordered probit model and the sequential logit model is the distribution assumption of the error terms of the response models. Since the normal distribution assumed in the Probit models does not have a closed form causing the difficulty of calculating the probabilities when integrating the probability density function, a distribution which is similar to the normal one and convenient to analyze was selected as an alternative. The selected distribution is the logistic distribution which is almost equivalent to the normal distribution except for its heavier tails. Thus, when the error term is assumed to be logistically distributed, the corresponding model is called logit model. (Ben-Akiva and Lerman, 1985)

4.3.1 Description of the Model Structure

Similar to the Markov process, the sequential logit model allows a pavement section to either stay in the current condition state or deteriorate to a worse state. In other words, a pavement section arrives at its current condition state by a sequential process, where the pavement sections begin to deteriorate from the condition state 0. Then, some of them deteriorate to condition states worse than condition state 0, others may stay in condition state 0. Among those sections deteriorated to the condition states worse than condition state 0, some of them may stay in condition state 1, while others continue to deteriorate to the condition states worse than condition state 1. The process keeps going on until the worst condition state K is reached. As such, the pavement deterioration process is considered as a series process of binary responses which is illustrated by Figure 4.3.

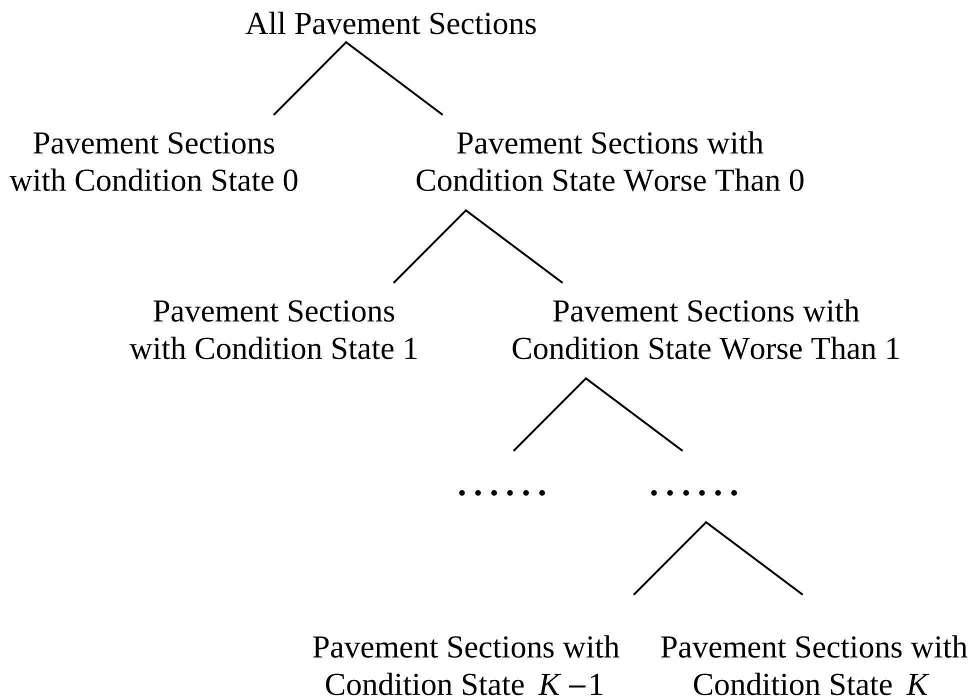

Figure 4.3 Structure of the Sequential Logit Model

Additionally, the sequential probabilities are analogous to the transition probabilities of the Markov process to some extent. Based on the sequential assumption, the deterioration of a certain pavement section in different condition states is dependent on its previous condition. Therefore, the transition probability of each binary response can be modeled using the sequence of the conditional probabilities as shown from Equation 4.15 to Equation 4.18, where condition state C_n for pavement section n is defined as the same as what has been defined in the ordered probit model.

$$q_0(X_n) = p(C_n = 0 \mid X_n) \tag{4.15}$$

$$q_1(X_n) = p(C_n = 1 \mid C_n \geq 1, X_n) \tag{4.16}$$

$$q_2(X_n) = p(C_n = 2 \mid C_n \geq 2, X_n) \tag{4.17}$$

……

$$q_K(X_n) = p(C_n = K \mid C_n \geq K, X_n) \tag{4.18}$$

The transition probability of each binary response can be estimated using a latent function, in which the propensity of pavement deterioration is explained by its explanatory variables. The utility function is represented as follows:

$$U_{in} = \beta_i' X_{in} + \varepsilon_{in} \tag{4.19}$$

where X_{in} is the set of the independent variables for binary response i;

i indicates the pair of binary responses represented by 0 to K correspondingly;

β_i is the corresponding parameters; and

ε_{in} is the error term.

The probability of pavement section n staying in condition state k is obtained by the following equation of the corresponding pair of binary response i, where $i = k$:

$$q_i(X_{in}) = \frac{\exp(\beta_i' X_{in})}{1 + \exp(\beta_i' X_{in})} \tag{4.20}$$

4.3.2 Maximum Likelihood Parameter Estimation of the Models

The parameters of the sequential logit model can be estimated by maximizing the likelihood function of each dichotomous case repeatedly (Amemiya, 1975). This parameter estimation process is based on the assumption that the utility function associated with any binary response is independent of any other utility functions in the sequential deterioration process, which facilitates the parameter estimation process by treating each binary response independently (Small, 1987). During the estimation process, the first estimation uses all of the observations because all of the pavement sections deteriorate from the “Very Good” condition state. For the subsequent binary responses, the observations are only limited to those pavement sections whose conditions are in the “Good” pavement condition state or worse. The estimation procedure is repeated for the remaining binary responses.

In order to estimate the parameters, the error term ε_{in} in each binary model is assumed to be independent identically distributed with logistic distributions. The pavement sections fall into condition state k if the latent variable U_{in} is positive and 0 otherwise. Hence,

$$C_{ni} = \begin{cases} 1 & if\ U_{in} > 0 \\ 0 & f\ U_{in} \leq 0 \end{cases}$$

Based on the independent assumption across observations, the likelihood function is:

$$L = \prod_{n=1}^{N} [1 - \Lambda(\beta_i^{'} X_{in})]^{1-C_{ni}} \Lambda(\beta_i^{'} X_{in})^{C_{ni}} \tag{4.21}$$

where Λ is the accumulated probability of the logistic distribution.

The corresponding log-likelihood function is:

$$L^{*} = \log L = \sum_{n=1}^{N} [(1 - C_{ni}) \log(1 - \Lambda(\beta_i^{'} X_{in})) + C_{ni} \log \Lambda(\beta_i^{'} X_{in})] \tag{4.22}$$

To obtain the estimates of the unknown parameters, the partial derivatives of Equation 4.22 are taken with respect to the unknown parameters. Then, the partial derivative of the log-likelihood function is set to zero and solved for the unknown parameters.

Once the parameters of the utility function for each dichotomous case are estimated, the probability of each condition state can be calculated by the production of the probabilities of the corresponding sequential binary models.

$$P_0(C_n = 0) = q_0(X_{0n}) \tag{4.23}$$

$$P_1(C_n = 1) = q_1(X_{1n})(1 - q_0(X_{0n})) \tag{4.24}$$

$$P_2(C_n = 2) = q_2(X_{2n})(1 - q_1(X_{1n}))(1 - q_0(X_{0n})) \tag{4.25}$$

……

$$P_K(C_n = K) = 1 - q_{K-1}(X_{K-1n})(\cdots(1 - q_1(X_{1n})(1 - q_0(X_{0n})) \tag{4.26}$$

The probabilities q_k are analogous to the transition probabilities of the Markov process to some degree. Some transitions between the condition states are excluded (Kahn and Morimune, 1979). For example, the transitions from the poor condition state to the good condition state are ruled out. That restriction is consistent with the realistic pavement deterioration process without the interruption of M&R treatments. In this case, the transition probability for pavement section n is defined as the probability of transitioning from one state to another in one time unit. The TPM is the matrix consisting of the transition probabilities defined as P_{ij}.

$$P_{ij} = P(C_n(t) = j \mid C_n(t-1) = i) \qquad (i, j = 0,1,2,\cdots,K)$$

where $C_n(t)$ and $C_n(t-1)$ indicate the condition states of pavement section n at time t and time $t-1$; and

P_{ij} indicates the transition probability from condition state i to condition state j.

The P_{ij} can be calculated based on Equation 4.27. If the probability of every possible transition is estimated, the TPM of a Markov Chain is developed.

$$P_{ij} = \begin{cases} \prod_{k=i}^{j-1} (1-q_k) \times q_j & i < j \\ q_i & i = j \\ 0 & i > j \end{cases} \qquad (i, j = 0,1,2,\cdots,K) \tag{4.27}$$

After developing the sequential logit model, three criteria: the adjusted likelihood ratio index $\bar{\rho}^2$ value defined by Equation 4.13, RMSE, and the average-percentage-of-correct-prediction defined by Equation 4.14 are also used to evaluate the goodness-of-fit of the developed models.

4.4 Summary

This chapter presents the methodology of utilizing an ordered probit model and a sequential logit model to characterize the stochastic characteristic of pavement deterioration by directly predicting pavement condition states. The ordered probit model is able to capture the uncertain nature of pavement deterioration, while the causal variables are linked to the condition states. The methodology of a sequential logit model mimics the pavement deterioration process. With this methodology, the time independent assumption for the pavement deterioration is eliminated by taking the impact of the previous condition states into account in terms of a sequential series, while the causal variables are also linked to the condition states. The application of the proposed methods is illustrated in the next chapter with case study examples.

CHAPTER 5 CASE STUDY OF PROBABILISTIC MODELS USING AASHO ROAD TEST DATA

As discussed in Chapter 4, the ordered probit model and the sequential logit model are used as the foundation of the probabilistic models. In order to demonstrate and evaluate the applicability of these proposed methodologies, a case study focused on applying the models with real data is presented in this chapter.

5.1 Selection of Case Study Data Set

The selection of appropriate data is important to a case study. Potential sources of data for applying these proposed probabilistic models range from the in-service pavement performance data (such as, the Long-Term Pavement Performance (LTPP) study, sponsored by FHWA) to the accelerated pavement tests data such as the AASHO Road Test data. In order to select the best data set for the case study, certain criteria were used to evaluate its appropriateness. These criteria are:

1) The data set should span the whole pavement deterioration process (i.e., from its brand new condition to its failure);
2) The data set should include the complete and detailed traffic information;
3) The data set should cover different pavement structural capacities; and
4) The data set should be recognized as being reliable by researchers.

Based on these criteria, the LTPP data and the AASHO Road Test data are the most promising data sets. Although the LTPP data set is more recent than the AASHO Road Test data, it cannot provide the complete and detailed traffic loading information. Since the purpose of this dissertation is to model pavement performance, complete and detailed traffic data is essential as the lack of these traffic data would make the development of performance models impossible. As a result, the AASHO Road Test data was selected for the case study, because it satisfies all the criteria; in addition, it is still the most reliable and fully controlled database in terms of the accurate traffic information.

5.2 AASHO Road Test

The AASHO Road Test was carried out in Ottawa, Illinois in the late 1950s (AASHO 1962). The purpose of the AASHO Road Test was to study the performance of flexible and rigid pavements under different combinations of pavement structures and traffic loadings. The location was selected based on the soil condition and climate zone which could represent most areas of the northern U. S. In this regard, the subgrade materials and the climate zone were fixed. Consequently, the experimental results cannot be used to evaluate the effects of subgrade materials and environment conditions different from those in the test without making appropriate adjustments. In the AASHO Road Test, the total number of flexible pavement sections was 332. No major maintenance was performed during the test period. All of the flexible pavement sections were three-layered structures. Among those layers, the surface thickness varied from 25.4 mm to 152.4mm(1 to 6 inches) with increments of 25.4mm (1 inch), the base thickness, 0 to 228.6mm(0 to 9 inches) with increments of 76.2 mm (3 inches), and the subbase thickness, 0 to 406.4 mm (0 to 16 inches) with increments of 101.6 mm (4 inches).

The tested pavements consisted of 6 loops. The traffic was applied on loop 2 to loop 6. In each loop, there was a four-lane divided highway, where each lane included different sections of 30.5mm (100 feet) in length. The traffic applied on each lane had the same axle configuration and the magnitude of loading. The speed of traffic was kept at 56 km/h (35mph). Table 5.1 shows the traffic loading configurations applied to each loop and each lane. From Table 5.1, it is easy to observe that different lanes and loops provided different traffic loadings. The traffic configurations included single axles and tandem axles. Twelve different combinations of axle configurations and magnitudes of loading were used in the test. The front axle load was not considered as the traffic loading in most of the cases except for lane 1 in loop 2 (AASHO, 1962).

In order to facilitate the case study, the effects of traffic loading have been standardized. The various axle loads were converted to the Equivalent Single Axle Load (ESAL) which is defined as the standard axle load based on the damage criteria (Huang, 1993). The AASHTO load equivalent factors (LEFs) were used to carry out the conversion. The axle load and the corresponding LEFs are listed in Table 5.1. Finally, only the ESAL is considered as the traffic-related variable.

Table 5.1 Axle Arrangements and Axle Load Configurations in the AASHO Road Test

Loop	Lane	Axle Configuration	Front Axle		Load Axle	
			Weight (KN)	LEF	Weight (KN)	LEF
2	1	1-1	8.9	0.00018	8.9	0.00018
2	2	1-1	8.9	0.00018	26.7	0.01043
3	1	1-1-1	17.8	0.00209	53.4	0.189
3	2	1-2-2	26.7	0.01043	106.8	0.26
4	1	1-1-1	26.7	0.01043	80.1	1
4	2	1-2-2	40.1	0.0562	142.4	0.857
5	1	1-1-1	26.7	0.01043	99.7	2.18
5	2	1-2-2	40.1	0.0562	178.0	2.08
6	1	1-1-1	40.1	0.0562	133.5	6.97
6	2	1-2-2	53.4	0.189	213.6	4.17

During the course of the experiment carried out from November 1958 to December 1960, the accumulated traffic and the corresponding PSI were recorded once every two weeks. Each record consists of the section inventory, layer thicknesses, the type of the base layer, PSI, the accumulated traffic trips, the index day for executing the measurement, and so on. As a result, 11,296 observations were obtained by pooling all of the observations together.

5.3 Establishment of the Pavement Condition States

Since pavement deterioration is the combined result of traffic loading, structural capacity, environmental factors, and other unobserved factors, all of these factors should be considered when modeling pavement deterioration. In order to capture the uncertainty of pavement deterioration, the continuous PSI is discretized into pavement condition states as discussed in Chapter 4. The scheme of discretizing the continuous PSI values stems from the initial method of developing PSI, where a 0-to-5 scale is used with 0 representing the very poor condition, and 5 the excellent condition. During the course of examining the measurement errors, it was found that the standard deviation of the ratings ranges from 0 to 0.5 with an average of 0.2 (Huang, 1993). Therefore, the PSI is evenly discretized into five condition states. Once the discrete pavement condition states are established, the ordered probit model and the sequential logit model can be applied.

If C_n represents the pavement condition states, it can be defined as follows:

$$C_n = \begin{cases} 0 & 4 \le PSI \le 5 \quad Very\ Good \\ 1 & 3 \le PSI < 4 \quad Good \\ 2 & 2 \le PSI < 3 \quad Fair \\ 3 & 1 \le PSI < 2 \quad Poor \\ 4 & 0 \le PSI < 1 \quad Very\ Poor \end{cases}$$

in which C_n can take the values from 0 to 4, depending on the condition of the pavement section. Although the real pavement condition may not deteriorate to state 3 and state 4 while the pavement is in service because of the applied M&R as remedies, the pavement performance model should be able to predict the complete deterioration process of the pavement. The percentages of each state in the AASHO Road Test are shown in Figure 5.1. As revealed by Figure 5.1, more than 50 percent of the pavement sections fall into the “Very Good” or “Good” condition. Around 20 percent of the sections fall into the “Fair” condition. The rest 10 percent of them fall into the worse conditions. Generally, the “Poor” and “Very Poor” conditions mean that the pavement has already failed.

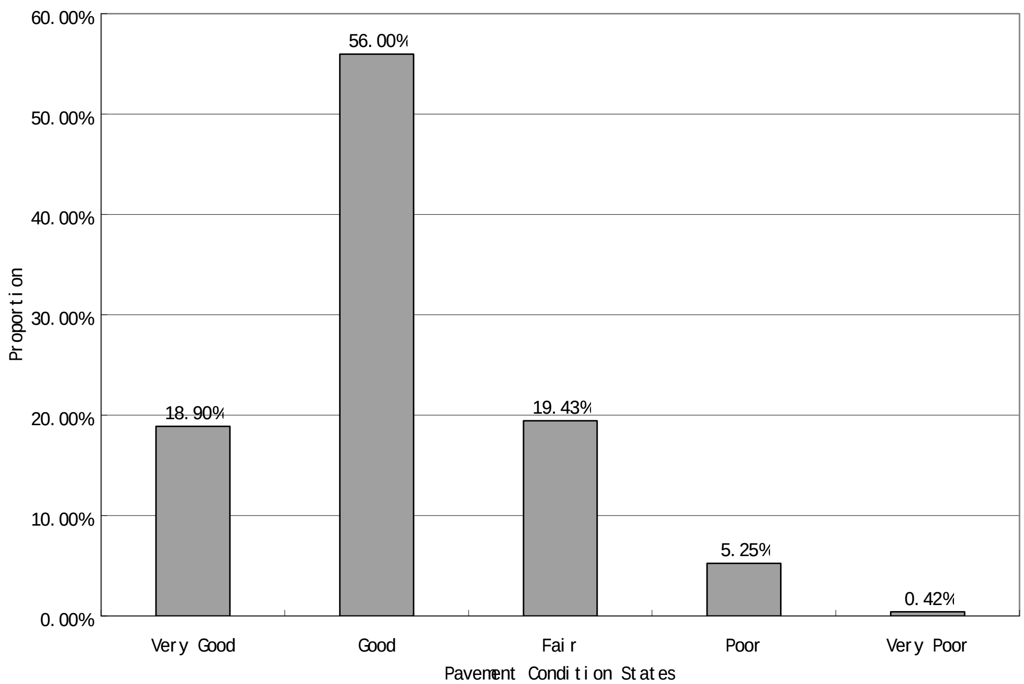

Figure 5.1 Sample Proportions of the Calibration Data Set

5.4 Preliminary Results of the Ordered Probit Model

To avoid using the same set of data for model calibration and validation, the total 11,296 observations were split into two parts through a random selection process. The first part of the randomly selected 9,099 observations was used to calibrate the model. The remaining 2,197 observations were used to validate the developed model.

Figure 5.2 shows the proportion of the data points used in the calibration and validation processes.

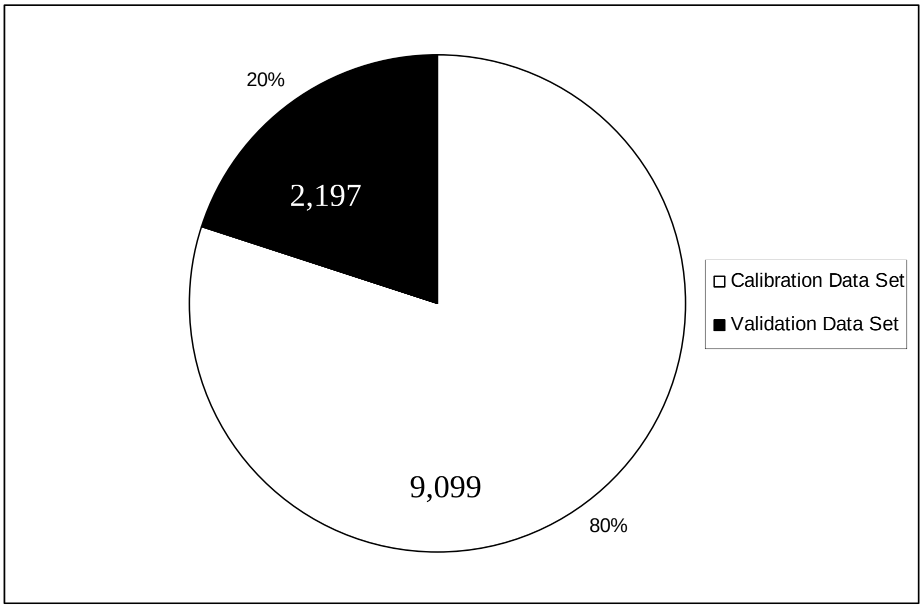

Figure 5.2 Calibration vs. Validation Data Set from the AASHO Road Test

Before estimating the pavement performance model, it is very helpful to introduce some prior knowledge of the pavement deterioration. Intuitively, the traffic-related variable has an impact on the pavement performance, so the traffic-related variable ESAL was included in the model. The structural capacity is related to the thickness of each layer. Generally speaking, the higher the structural capacity, the lower the pavement deterioration rate is. In this case, the thickness of each layer was used to represent the structural capacity. Environmental factors also affect the performance. For example, even if there is no traffic loading applied on the pavement, there is still loss of serviceability with time. This phenomenon is because of the impact of temperature and moisture. However, since all of the pavement sections in the

AASHO Road Test were in the same location, it is hard to capture the exact effects of different temperature and moisture in different climate zones. As a result, the impact of the spring season was used to represent the effects of the temperature and moisture. More specifically, a year was divided into the spring period and the non-spring period based on the AASHO road test report. The spring season covers the period from the middle of February to the beginning of June (AASHO, 1962). A dummy variable of the spring seasonal factor is defined based on this division. The dummy variable was assigned 1 if it was the spring, and 0 otherwise. Observations showed that the freeze-thaw cycles caused significant changes in the serviceability in the spring when comparing with other seasons. The reason is that the subgrade is stronger in the winter but much weaker in the spring. In summary, X_n in Equation 5.1 consists of the surface thickness (D_s), base thickness (D_b), ESAL (T_{ESAL}), and the spring seasonal factor (S). Therefore, the explanatory variables are defined as a vector $X_n = \{1, D_s, D_b, T_{ESAL}, S\}$. Their corresponding parameters are defined as another vector $\beta = \{\beta_0, \beta_1, \beta_2, \beta_3, \beta_4\}$. Then three thresholds are defined as $0 \le \Psi_1 \le \Psi_2 \le \Psi_3$. The ordered response model can be written as:

$$U_n = \beta_0 + \beta_1 D_s + \beta_2 D_b + \beta_3 T_{ESAL} + \beta_4 S + \varepsilon_n \tag{5.1}$$

And the probability in each state can be calculated as follows:

$$P(C_n = 0) = \Phi(-\beta' X_n) \tag{5.2}$$

$$P(C_n = 1) = \Phi(\Psi_1 - \beta^{'} X_n) - \Phi(-\beta^{'} X_n) \tag{5.3}$$

$$P(C_n = 2) = \Phi(\Psi_2 - \beta^{'} X_n) - \Phi(\Psi_1 - \beta^{'} X_n) \tag{5.4}$$

$$P(C_n = 3) = \Phi(\Psi_3 - \beta^{'} X_n) - \Phi(\Psi_2 - \beta^{'} X_n) \tag{5.5}$$

$$P(C_n = 4) = 1 - \Phi(\Psi_3 - \beta^{'} X_n) \tag{5.6}$$

With the defined response variable C_n and the set of the explanatory variables X_n, the ordered probit model is estimated with the LIMDEP (Greene, 1998) as the analysis software. The estimation results are summarized in Table 5.2. All of the estimated parameters shown in Table 5.2 are statistically significant at the 0.05 significance level.

As revealed in Table 5.2, all of the signs for parameters are consistent with prior expectations. Among those layer thicknesses, the most important factor impacting the pavement performance is the surface thickness. Based on the above model, the negative sign of the surface thickness means that the increase of the surface thickness increases the probability of the pavement staying in very good performance condition. Similarly, the negative sign of base thickness also implies that a thicker base layer can decrease the degree of the pavement damage. However, based on the magnitude of coefficients, its impact on deterioration is not as large as the surface thickness. Another observation worth noting is that both layer thicknesses have negative coefficients in the model. This result is expected since both of them contribute to the structural capacity of the pavement.

Table 5.2 Parameter Estimation for Ordered Probit Model

Variables	Parameters of Variables	Standard Error	t-statistics
Constant	1.19379	0.0454795	26.249
D_s	-0.10967	0.0102503	-10.700
D_b	-0.01859	0.00460553	-4.035
T_{ESAL}	3.00657e-007	9.08601e-009	33.090
S	0.05729	0.0270157	2.121
Ψ_1	1.67585	0.0198802	84.297
Ψ_2	2.66006	0.0262598	101.298
Ψ_3	3.76197	0.0571374	65.841
Statistic Summary L(C)=-10332.91 L(B)=-9765.08 $\bar{\rho}^2$ =0.0543			

The traffic variable contributes to increasing the degree of the pavement condition deterioration, given its positive sign. When the pavement approaches the end of its design life, the overall condition gets worse. The positive sign of the spring seasonal factor means the pavement sections are more likely to be deteriorated in the spring than in the other seasons. The reason is that the pavement becomes much weaker in the spring than in the winter because of the excessive water from the melting of ice in the spring-thaw period when the probability of severe pavement damage is high, especially with the passing of heavy duty trucks.

As discussed in the previous section, 2,197 observations were used to validate the developed model. The probabilities in each condition state for all of the observations in the validation data set were averaged in order to obtain the aggregate probabilities or percentages for the corresponding condition state. In order to examine the accuracy of the prediction, the observed frequency and the average percentage for each condition state in the validation data set were calculated. Table 5.3 shows the predicted and observed percentages falling into each condition state in the validation data set. As shown in Table 5.3, the maximum difference between the predicted proportions and the observed proportions is 1.85 percent. Therefore, the predicted value is very close to the observed value for each of the condition states in the validation data set, given that the validation data set is completely separated from the estimation data.

Table 5.3 Descriptive Statistics on Each State in the Validation Data Set

Condition State	Observed Frequency	Observed Percentage (%)	Predicted Percentage (%)	Difference (%)
0	421	19.16	18.60	-0.56
1	1,217	55.36	56.80	1.44
2	450	20.48	18.63	-1.85
3	96	4.37	5.24	0.87
4	13	0.59	0.72	0.13

In addition to the validation results, several other statistical parameters were used to evaluate the model. From Table 5.2, the adjusted likelihood ratio index $\bar{\rho}^2$ is small. The reason for this small value is related to the variances of deterioration in the data set. Additionally, the unavailability of some explanatory variables in the data set could be another reason. But given that the adjusted likelihood ratio index $\bar{\rho}^2$ cannot indicate the correctness of the prediction, the model should be further tested by checking other goodness-of-fit indicators such as the RMSE values.

In order to further verify the developed model, the average-percentage-of-correct-prediction $\overline{P}$ at the disaggregate level is calculated by using the previously explained Equation 4.14. The calculated $\overline{P}$ value is 0.5325. At the same time, the calculated RMSE at the aggregate level is 1.15 percent. The average-percentage-of-correct-prediction at the disaggregate level seems relatively low, since it is based on the maximum utility assumption. In this case, the stochastic problem is transferred back to the deterministic problem, causing the relatively lower average-percentage-of-correct-prediction. As a matter of fact, it is misleading only to compare the predicted condition state based on the highest probability with the observed pavement condition (Horowitz, 1982). However, the prediction error at the disaggregate level can be averaged out at the aggregate level. Consequently, the RMSE at the aggregate level is 0.26 percent which indicates a very small difference between the predicted pavement condition states and the actual condition states. Therefore, the ordered probit model can be used as a reliable tool to predict the probabilities of the pavement condition states. That advantage benefits the pavement prediction because of the uncertainty nature in the pavement deterioration process.

5.5 Preliminary Results of the Sequential Logit Model

The AASHO Road Test data is also used to calibrate and validate the sequential logit model. The explanatory variables are defined as the same as the ordered probit model, consisting of the surface thickness (D_s), base thickness (D_b), subbase thickness

(D_{sb}), ESAL (T_{ESAL}), and the spring seasonal factor (S). Similar to the calibration and validation process of developing the ordered probit model, the same 9,099 observations are used to calibrate the sequential logit model, while the remaining 2,197 observations are used to validate the developed sequential logit model. The model specification is given in Table 5.4.

As revealed by Table 5.4, the binary model of the "Very Good" pavement condition state includes all of the explanatory variables. But the rest of the binary logit models do not include all of them. Furthermore, the same explanatory variable in the different binary logit models may have signs opposite to expectation. This situation is probably caused by the parameter estimation process, since the subsequent binary logit model is determined conditionally on its previous conditions. For example, the binary logit model for the pavement condition state "Good" is estimated using the data set in which all of the pavement sections have the pavement condition state worse than "Very Good". Therefore, it is not easy to make straightforward explanations only based on the signs and magnitudes of the parameters, especially in the subsequent binary logit models. But the interpretation for the parameters of the binary logit model in the "Very Good" condition state is possible, since the binary logit model is not dependent on any previous condition states.

Table 5.4 Sequential Logit Model Specifications of the Pavement Performance

	Very Good		Good		Fair		Poor	
Variable	**Coefficient (t statistics)**	**Standard Error**	**Coefficient (t statistics)**	**Standard Error**	**Coefficient (t statistics)**	**Standard Error**	**Coefficient (t statistics)**	**Standard Error**
Constant	-2.8709 (-26.1950)	0.1096	0.7516 (-8.5220)	0.0882	2.2027 (10.9735)	0.2007	3.7721 (4.6224)	0.8160
D_s	0.3395 (11.7795)	0.0288	0.1626 (6.4230)	0.0253	-0.0862 (-1.7668)	0.0488	-0.5049 (-2.9249)	0.1726
D_b	0.1020 (8.9806)	0.0114	________	________	________	________	________	________
D_{sb}	0.0895 (11.0503)	0.0081	-0.0203 (-2.9213)	0.0070	-0.0846 (-5.8211)	0.0.0145	0.1005 (1.9312)	0.05204
T_{ESAL}	-2.83E-06 (-27.530)	1.19E-07	-3.72E-07 (-18.3988)	2.02 E-08	1.01E-07 (3.02812)	3.33E-08	________	________
S	-0.2471 (-3.7879)	0.0652	________	________	________	________	________	________
Sample Size	1720		5095		1768		478	
L(c)	-4411.340		-4565.548		-1220.3380		-135.6889	
L(B)	-3624.357		-4322.292		-1197.0040		-130.6791	
Rho-squared	0.1770		0.0524		0.0158		0.0148	

The explanation of each variable is similar to that in the ordered probit model. Moreover, it is also noticed that the traffic-related variable ESAL is not significant in the binary logit models of the “Fair” and “Poor” condition states. The reason might be that the pavement sections in the above two states are near failure or have already failed; therefore, the increase of the ESAL would not contribute to any significant change in the pavement deterioration propensity. The goodness-of-fit parameters discussed in Chapter 4 are also used to evaluate the developed sequential logit model. The adjusted likelihood ratio index $\bar{\rho}^2$ for the first binary response is large relative to the rest of the four binary responses, although all of them are not absolutely high.

As discussed briefly earlier, 2,197 observations are used to validate the developed model. Table 5.5 shows the validation results of the sequential binary logit models. The predicted values are very close to the observed. The maximum prediction error is 4.12 percent. The RMSE is 2.42 percent. Both of the numbers indicate that the aggregate predictions are very close to the actual observations.

Table 5.5 Validation Results for Transition Probabilities in Each Binary Case

Condition State	Observed Frequency	Observed Percentage (%)	Predicted Percentage (%)	Difference (%)
0	421	19.16	18.62	0.54
≥ 1	1217	68.52	70.26	-1.74
≥ 2	450	80.50	77.52	2.98
≥ 3	96	88.07	92.20	-4.12
≥ 4	13	1	1	0

Table 5.6 shows the observed and predicted proportions of each condition state in the validation data set. As can be seen, the aggregate predicted proportions are also close to the actual observed proportions. The maximum prediction error is about 1.78 percent. At the same time, the prediction error increases when conditions deteriorate from “Very Good” to “Fair”. This increase is related to the error propagation caused by the production process. Furthermore, the prediction error could be related to the estimation bias resulting from the independent assumption of the parameter estimation method of the sequential binary responses. The independent assumption causes the bias of the parameter estimation because of the heterogeneity of the observations. For example, the unobserved characteristics in the data set used to estimate the probability q_0 may be different from those in the data set used to estimate the probability q_1. The extent of bias is related to the correlation between those unobserved characteristics (Kahn and Morimune, 1979). The average-percentage-of-correct-prediction $\overline{P}$ at the disaggregate level is 0.5972, calculated using the previously explained Equation 4.14. The calculated RMSE in this validation process is 1.18 percent. Therefore, the sequential logit model also demonstrates good prediction accuracy.

Table 5.6 Validation Results for Probability in Each Condition State

Condition State	Observed Frequency	Observed Percentage (%)	Predicted Percentage (%)	Difference (%)
0	421	19.16	18.62	0.54
1	1217	55.39	57.18	-1.78
2	450	20.48	18.76	1.72
3	96	4.37	5.02	-0.65
4	13	0.59	0.39	0.20

Since the probability of condition state is developed based on previous condition states, the TPM can be easily estimated with the developed sequential model using Equation 4.27.

Figure 5.3 demonstrates the probability changes of a pavement section for all of the condition states over time. In this case, the means of the explanatory variables are used in these developed models to determine probability trends. As can be seen, the probability of the “Very Good” condition state steeply falls when more and more traffic is applied on the pavement, then the probability remains steady after the volume of the traffic approaches a certain value. This is because traffic loading significantly contributes to damaging the excellent pavement condition. As a result, the probability of staying in the “Very Good” condition state decreases over time. The probability curve of staying in the “Good” condition state begins with an increase trend until it reaches its peak and then falls off. That trend makes the probability curve look like an uncompleted bell. The other three probability curves keep increasing but with different slopes when the traffic increases. These trends illustrated by Figure 5.3 assist pavement management personnel in directly providing the probabilities in each pavement condition state given a combination of the explanatory variables. These probabilities can also be explained as the reliability progression of a pavement section with time or even further extended to the reliability-based analysis. Thus, the decision-makers of pavement management can more effectively allocate limited resources to achieve the maximal benefits.

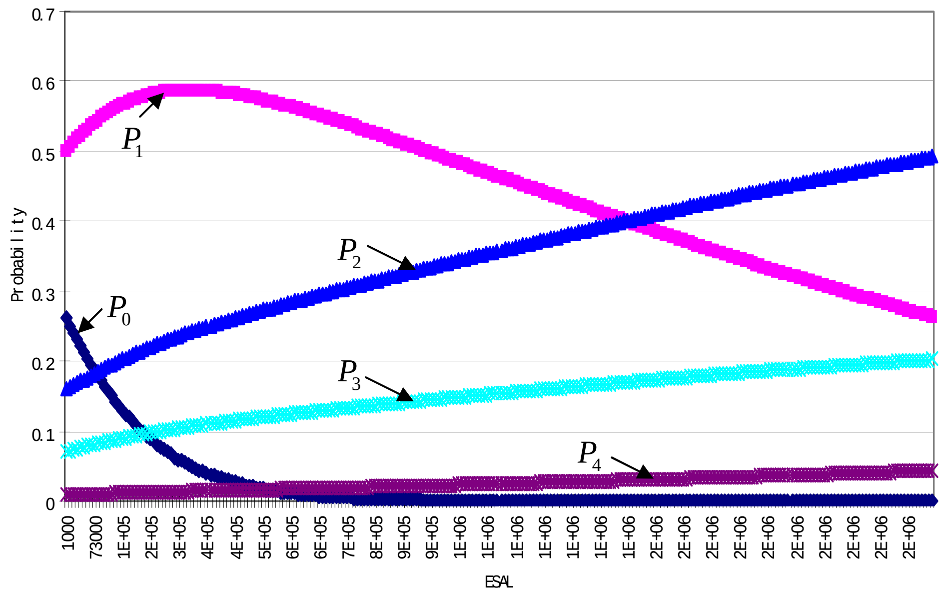

Figure 5.3 Probability Changes of Five Pavement Condition States over Traffic

5.6 Development of Mechanistic-Empirical Models

All of the previously developed models in this chapter are based on the empirical approach. They are limited by local environmental conditions, materials, pavement types, and vehicle characteristics in the AASHO Road Test. The developed relationships are only valid for the test situation and cannot be applied to other situations without appropriate adjustments. In addition, since no major maintenances were applied on the pavement sections during the AASHO Road Test, the impact of M&R treatments cannot be accommodated with these relationships.

5.6.1 Identification of Primary Response Variables

In order to extend the inference space of the AASHO Road Test beyond its original testing conditions, a mechanistic-empirical approach is taken to relate the mechanical responses of a pavement such as stress and strain to its performance. This mechanistic-empirical approach has been used in research studies such as the recently developed Guide for Mechanistic-Empirical Design of New and Rehabilitated Pavement Structures (TRB, 2005), British pavement design method (Lister and Powell, 1987), and the evaluation of the AASHTO LEFs for changing traffic characteristics (Kawa, 2000).

Based on the previous research, three primary responses are normally used in analyzing pavement performance:

1) Surface deflection;
2) Horizontal tensile strain at the bottom of the surface layer; and
3) Vertical compressive strain at the top of subgrade.

Figure 5.4 illustrates the primary responses of a flexible pavement. Once these responses are accumulated to their limits, structural damage of pavement occurs. The accumulated damage history represents pavement performance, since pavement performance is a time-related concept. Therefore, these three primary responses variables are able to represent the mechanistic processes of pavement deterioration.

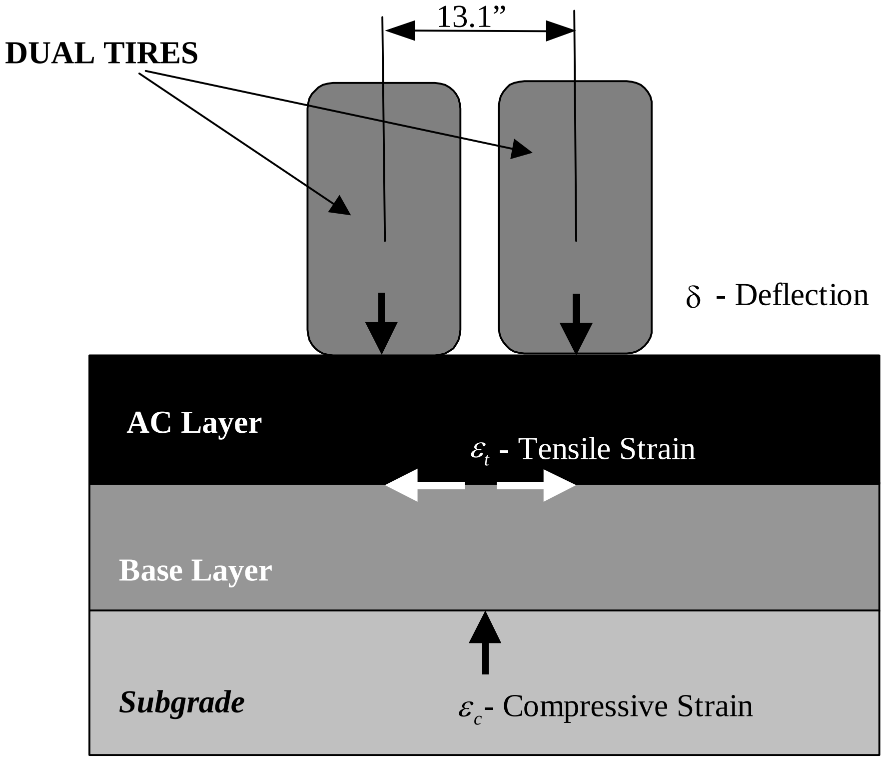

Figure 5.4 Critical Primary Responses in Flexible Pavement Structure

5.6.2 Development of Mechanistic-Empirical Models

The statistical technique used to develop mechanistic-empirical models is the same as the empirical models except for the inclusion of these primary response variables as part of the explanatory variables. The whole development process consists of the five steps: 1) identify a computer program to calculate the primary responses; 2) obtain the parameters required by the selected program; 3) calculate the primary responses; 4) estimate the model specification using the statistical program Limdep; and 5) evaluate the developed models.

Normally, the primary responses analysis of the flexible pavement is based on the elastic layer theory which assumes the static, uniform, and circular load pattern. Research conducted by Lister shows that this load assumption causes only less than two percent of errors comparing with the realistic load (Lister, 1967). Therefore, the elastic assumption is acceptable in this research. Based on the elastic layer theory, the primary responses of a flexible pavement can be calculated using different computer programs. Among commonly used computer programs such as KENLAYER, ELSYM5, and Abaqus, the results provided by KENLAYER and ELSYM5 are almost the same, whereas Abaqus produces relatively lower responses when using a pavement structured with a 6-inch thick AC layer and a 10-inch thick base layer (Kawa, 2000). Since Abaqus is more complicated to use, KENLAYER was chosen to calculate the primary responses for this research.

Once the computer grogram is selected for the calculation, the parameters have to be determined. The magnitude and specification of the traffic loading are illustrated in Table 5.1. Material moduli of elasticity for flexible pavement sections are determined from a report written by Irick (Irick, 1991). The Poisson's ratio is obtained based on the material characteristics of experiments. Table 5.7 gives the values of these parameters.

Table 5.7 Poisson's Ratios and Material Characteristics

Layer	Modulus (psi)	Poisson's Ratio
AC	742,500	0.3
Base	20,400	0.35
Subbase	17,000	0.4
Subgrade	10,700	0.45

Another important parameter is the tire contact area. Normally, the contact tire pressure is assumed to be uniformly distributed and equal to the actual tire pressure. Based on the circle contact area assumption of KENLAYER, the radius of the contact area was calculated according to the following formula:

$$R = \sqrt{A_c / \pi} \tag{5.7}$$

where A_c can be obtained by dividing the load on each tire with the tire pressure. Figure 5.5 illustrates the actual contact area and the approximated equivalent circular contact area.

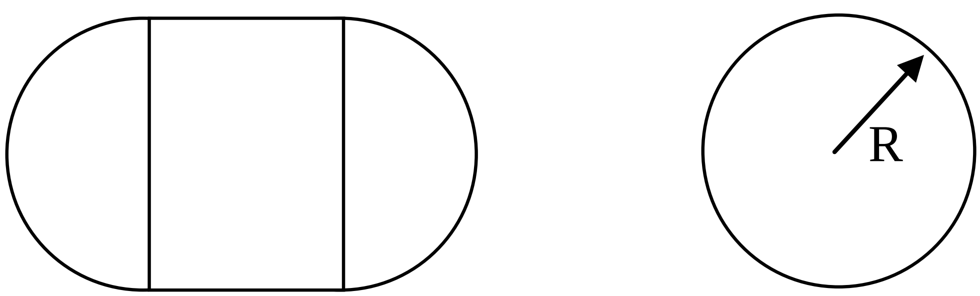

Figure 5.5 Dimension of Tire Contact Area (Huang, 1993)

After determining these parameters, the primary responses were calculated using KENLAYER. Since the methodologies of developing the ordered probit model and the sequential logit model are tested as being valid based on their prediction capability, the same modeling procedure was employed to develop the mechanistic-empirical models. The explanatory variables include the SN, magnitude of axle load (L), deflection of the pavement surface (δ), horizontal tensile strain at the bottom of the surface layer (ε_t), compressive strain at the top of the subgrade (ε_c), accumulated traffic loadings (n), and the spring seasonal factor (D_s). The data set used to estimate the parameters of the ordered probit model was the same calibration data set including 9,099 observations. The final model specification for the mechanistic-empirical ordered probit model is shown in Table 5.8 after estimation by the Limdep.

Table 5.8 Mechanistic-Empirical Model Specification of the Ordered Probit Model

Variables	**Parameters of Variables**	**Standard Error**	**t-statistics**
Constant	-0.2766	0.04511	-6.1307
n	2.58E-06	5.57E-08	46.2665
L	9.36E-06	7.98E-07	11.7269
D_s	0.12925	0.02438	5.30062
ε_t	2142.91	175.696	12.1966
Ψ_1	1.76354	0.01888	93.4214
Ψ_2	2.79993	0.02476	113.106
Ψ_3	3.87989	0.05169	75.0577
Statistic Summary L(C)=-12898.54 L(B)=-11838.87 $\bar{\rho}^2$=0.0816			

Similarly, the mechanistic-empirical sequential logit method was also developed using the Limdep. The final model specification is shown in Table 5.9.

Table 5.9 Mechanistic-Empirical Model Specification of Sequential Logit Methodology

	Very Good		Good		Fair		Poor	
Variable	**Coefficient (t statistics)**	**Standard Error**	**Coefficient (t statistics)**	**Standard Error**	**Coefficient (t statistics)**	**Standard Error**	**Coefficient (t statistics)**	**Standard Error**
$Constant$	-0.4630 (-3.5953)	0.1288	3.3472 (22.7912)	0.1469	2.4645 (9.7727)	0.2522	-2.8924 (-61.5526)	0.0470
SN	0.3942 (9.9532)	0.0396	0.1690 (4.4205)	0.0382	———	———	———	———
L	-2.91×10^{-5} (-9.0167)	3.22×10^{-6}	-2.92×10^{-5} (-9.8722)	2.96×10^{-6}	-2.29×10^{-5} (-5.6362)	4.06×10^{-6}	———	———
n	-7.47×10^{-6} (-26.6546)	2.81×10^{-7}	-3.79×10^{-6} (-25.0706)	1.51×10^{-7}	———	———	———	———
D_s	-0.2691 (-4.1826)	0.0643	-0.1644 (-2.6231)	0.0627	———	———	———	———
ε_t	-2070.56 (-4.5426)	455.814	-5788.7 (-12.9538)	446.874	-2212.73 (-2.5390)	871.484	———	———
Sample Size	1720		5095		1768		478	
L(c)	-4411.340		-4565.548		-1220.338		-1873.554	
L(B)	-3773.220		-4092.074		-1199.047		-1873.554	
Rho-squared	0.1435		0.1026		0.0158		0.0000	

Table 5.10 illustrates the goodness-of-fit of the developed mechanistic-empirical models. It is not difficult to find that the predicted and the observed results are very close. The RMSEs of the ordered probit model and the sequential logit model are 0.83 and 0.70 percent respectively. Both of the goodness-of-fit parameters indicate that the mechanistic-empirical models are acceptable.

Table 5.10 Validation Results for Probabilities Calculated using Mechanistic-Empirical Models in Each Condition State

Condition State	Observed Frequency	Observed Proportion (%)	Predicted Proportion (%)	
			Ordered Probit	Sequential Logit
0	421	19.16	19.00	18.98
1	1217	55.39	56.30	56.11
2	450	20.48	19.04	19.35
3	96	4.37	5.07	5.15
4	13	0.59	0.58	0.38

5.7 Summary

This chapter presents the calibration and validation results of the ordered probit models and the sequential logit models using the AASHO Road Test data. The calibrated ordered probit model demonstrates that the methodology is able to provide reliable prediction of pavement condition states regardless of whether deterioration process is homogenous or not. Furthermore, directly predicting the probabilities of the pavement condition states is effective for depicting the stochastic deterioration process, as the methodology eliminates the need for the TPMs. The validation results of sequential logit model also indicate that it can yield reliable prediction of pavement condition states by means of the production of a sequence of binary logit probabilities. During this process, the transition probabilities between any two condition states can be easily calculated by considering the conditional probabilities in the sequential series. This process makes the estimation of the TPM more straightforward in comparison with other methods. Then, the ordered probit model and the sequential logit model are extended using the mechanistic-empirical approach to incorporate primary response variables into explanatory variables. The validation results also show good prediction accuracy of these mechanistic-empirical models.

CHAPTER 6 COMPARISON OF PROPOSED PROBABILISTIC MODELS AND EXISTING PROBABILISTIC MODELS

As presented in Chapter 5, the ordered probit models and the sequential logit models have the ability to yield good prediction results. However, the performance of these two models in comparison with other probabilistic models is still unknown. Therefore, this chapter is devoted to select widely accepted probabilistic models and compare them with the developed ordered probit models and sequential logit models, using the same AASHO Road Test data set.

6.1 Selection of Existing Probabilistic Models for Comparison

Currently, the homogeneous (Wang et al., 1994), or non-homogeneous Markov Chains (Jiang et al., 1987; Butt et al., 1987), and the duration models (Prozzi and Madant, 2000) are considered as accepted probabilistic models of modeling pavement performance based on the literature review in Chapter 2. These three methods are selected as alternative models of the developed probabilistic models. Since the ordered probit models and the sequential logit models were developed based on the AASHO Road Test data, it is also taken as the data set for the comparisons. For these selected models, although the duration model (Prozzi and Madant, 2000) was developed based on the AASHO Road Test, there is no Markov Chain models developed with the same data set. Therefore, the homogenous and non-homogeneous Markov Chain models need to be developed in order to make comparisons.

6.2 Developing TPMs for Markov Chain Models

The Markov Chain models have been proved as an effective tool to characterize the pavement deterioration process since 1982 (Goliba, 1982). As discussed in Chapter 2, the key to a Markov Chain model is the development of the TPM. Currently, two approaches are employed to develop TPMs. The first approach, which is the simplest one, directly calculates the transition probabilities based on the time independent assumption. The transition probability from state i to state j is calculated using the proportion of pavement sections deteriorated from state i to state j, which is shown in Equation 6.1 (Wang et al., 1994):

$$p_{ij} = \frac{m_{ij}}{m_i} \tag{6.1}$$

where p_{ij} is the transition probability from state i to state j;

m_{ij} is the total number of pavement sections whose condition states change from state i to state j; and

m_i is the total number of pavement sections whose initial condition states are i.

The second method of developing TPMs is the expected-value method which is able to estimate the TPMs of both the homogeneous and non-homogeneous Markov

Chain models. For the non-homogeneous Markov Chain models, pavement sections are arranged into different groups based on their attributes to remove the non-homogeneous property associated with their relative variables. Then, the linear regression model of condition ratings is estimated for each group as (Madanat et al., 1995):

$$Y_n = \beta_1 + \beta_2 t_n + \varepsilon_n \tag{6.2}$$

where Y_n is the PSI of pavement section n;

t_n is the age of pavement section n;

β_1, β_2 are parameters to be estimated; and

ε_n is the random error term.

The TPM is estimated for each group by minimizing the distance between the expected value of the pavement condition predicted by the linear model and the theoretical expected value derived from the Markov Chain model. The mathematical representation of the minimization of the distance between the two expected values is as follows:

$$Min\ \ W = \sum_{t=\tau}^{\tau+\Delta T-1} \left| \hat{Y}_t - E(t, p) \right| \tag{6.3}$$

Subject to: $0 \le p_{ij} \le 1; i, j = 1,2,\cdots k$

$$\sum_{j=1}^{k} p_{ij} = 1; i = 1,2,\cdots k$$

where $E(t, p)$ is the expected value of pavement condition at age t as a function of Markov transition probabilities;

$\hat{Y}_t$ is the average condition rating for pavement sections in a group at age t;

τ is the earliest age observed in the group under consideration; and

ΔT is the number of years in the group of pavement sections under consideration.

This method estimates TPMs of each group by treating them as a homogeneous process. Under this assumption, the probabilities falling into certain condition states are calculated. Although other econometric methods have been used for developing non-homogeneous TPMs (Madanat et al., 1995), they are relatively complicated to develop and are difficult to compare because of the violation of the Markov time-independent assumption.

6.3 Duration Model

The duration model was developed to model the failure times of pavement sections by Prozzi and Madanat in 2000 (Prozzi and Madanat, 2000). The duration model considers the variability of failure times and the unobserved failure events in pavement failure experiments by representing the failure times with probability density functions other than deterministic values.

This method is similar to modeling a process with the unit of measurement on the time axis. In this case, the traffic loading is equivalent to the measurement time indicating the life of pavements. Hazard rate λ_n of pavement section n is defined as a function of explanatory variables shown in Equation 6.4. The parameter θ is estimated using the maximum likelihood estimation method which addresses the censored problems associated with the collected data. The researchers selected a Weibull distribution to represent failure times.

$$\lambda_i = \exp(-\theta_i X_i) \tag{6.4}$$

The Weibull hazard function representing failure times is shown in Equation 6.5. The hazard rate can increase or decrease depended on the value of parameter p. If p approaches to 1, the deterioration process can be modeled using a Markov Chain process. That is to say, the deterioration process is not related to time and vice versa.

$$\lambda(t) = \lambda p(\lambda t)^{p-1} \tag{6.5}$$

After conducting the analysis based on the AASHO Road Test data, the final model format was estimated shown by Equation 6.6.

$$E[\rho] = \frac{10^{5.28}(D+1)^{6.68} L_2^{2.62}}{(L_1 + L_2)^{3.03}} \tag{6.6}$$

where ρ is the ESAL required to produce a damage level defined as failure;

D is the structural number of the pavement sections;

L_1 is the axle load in kips; and

L_2 is the dummy variable (equals to 1 for single axles; equals to 2 for tandem axles).

Since Equation 6.6 can only calculate the number of ESAL load repetitions to failure, Equation 6.7 is used to relate it to pavement condition index PSI. It is worthy of mentioning that Equation 6.7 and 6.8 were developed by the AASHO (AASHO, 1965) other than Prozzi and Madanat. Therefore, it may cause the calculation inconsistency in the validation process.

$$PSI = 4.5 - 3.0 \times \left(\frac{W}{\rho} \right)^{\beta} \tag{6.7}$$

where $$\beta = 0.4 + \frac{0.08(L_1 + L_2)^{3.23}}{(D_1 + 1)^{5.19} L_2^{3.23}} \tag{6.8}$$

W represents the current observed traffic loading.

6.4 Determination of Comparison Criteria

In order to compare different probabilistic models, different criteria are identified. The most straightforward criterion is to compare the predicted proportions with the observed ones. The second criterion is the RMSE between the observed pavement conditions and the expected values which are defined as the weighted average of each condition state. During that process, the mean of each condition state is taken as the representative value of this condition state because of the even discretization scheme and the physical meaning of the PSI. The RMSE is obtained by calculating the root mean square between the observed and expected pavement conditions.

The third criterion is the chi-squared goodness-of-fit test which is used for measuring the closeness of the predicted and the observed values (Jiang et al., 1987). The chi-squared value is calculated by:

$$\chi^2 = \sum_{n=1}^{N} \frac{(R_n - E_n)^2}{E_n} \tag{6.9}$$

where k is the number of observations;

R_n is recorded value of the n^{th} observation;

E_n is expected value of the n^{th} observation; and

χ^2 has a chi-square distribution with $k-1$ degree of freedom.

6.5 Comparison Procedure and Evaluation of Results

The methodologies of homogeneous and non-homogeneous Markov Chains and the duration model are described in Chapter 6. This section presents comparison procedure and comparison results. The whole procedure is illustrated in Figure 6.1. First, the AASHO Road Test data set is selected as the data to conduct this analysis as discussed in Chapter 6. Then, two Markov Chain models are calibrated to make predictions in the same way as the other three developed probabilistic models did. Next, three criteria are implemented to compare these five models. Finally, conclusions are made based on the comparison results.

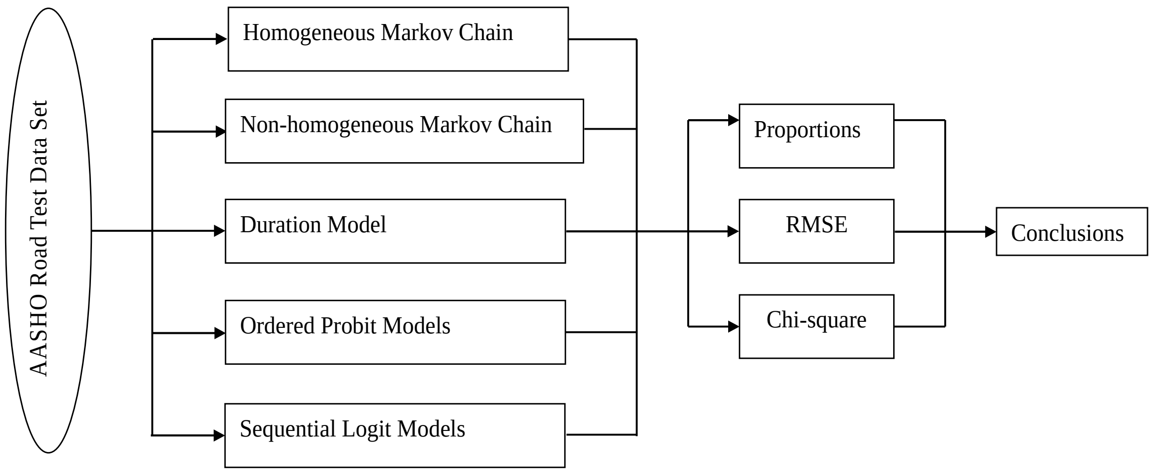

Figure 6.1 Flowchart for Conducting the Comparison

In order to make the Markov Chain models consistent with the probit and logit model, the same calibration data set is used to calibrate these models; and the same validation data set is used to make comparisons. The homogeneous Markov Chain model is developed based on the calibration data set. The TPM is estimated using Equation 6.1 and shown in Table 6.1. Once the TPM is developed, the Markov Chain model is used to predict the probabilities of each condition state based on the validation data set. The final calculation results are given in Table 6.3.

Table 6.1 Transition Probability Matrix

Condition State	**0**	**1**	**2**	**3**	**4**
0	0.7164	0.279	0.0038	0.0005	0
1	0	0.9157	0.0801	0.0036	0.0007
2	0	0	0.9046	0.0921	0.0032
3	0	0	0	0.9533	0.0467
4	0	0	0	0	1

Then, the expected-value method is used to develop the TPMs of the non-homogeneous Markov Chain model. In order to better estimate the transition probabilities, pavement sections subject to similar traffic loadings are classified into one group. Since pavement sections located on the same loop and the same lane were loaded with the same traffic during the AASHO Road Test, the pavement sections are arranged into 10 groups. Then, for each group, the regression model is developed based on the calibration data set. The regression results are illustrated in Table 6.2. As it can be seen, the R^2 values are small, indicating that the developed models do not explain the dependent variable PSI very well. The reason behind this phenomenon is that, in addition to time, there are other variables that contribute to the pavement deterioration as well, meaning the current 10 groups should be further stratified to remove the non-homogeneity of the explanatory variables. This leads to the limitations of the expected-value method.

Table 6.2 Regression Model of Each Group

Group	Regression Function	R Square
Loop 2 Lane 1	$y = 0.0002x^2 - 0.018x + 3.7471$	0.1179
Loop 2 Lane 2	$y = 6E\text{-}05x^2 - 0.0225x + 3.6934$	0.289
Loop 3 Lane 1	$y = -5E\text{-}05x^2 - 0.0173x + 3.7783$	0.2641
Loop 3 Lane 2	$y = -0.0073x + 3.5871$	0.0528
Loop 4 Lane 1	$y = -0.0231x + 3.9955$	0.3416
Loop 4 Lane 2	$y = -0.0241x + 3.9014$	0.3172
Loop 5 Lane 1	$y = -0.0207x + 3.8739$	0.229
Loop 5 Lane 2	$y = -0.0226x + 3.6791$	0.2495
Loop 6 Lane 1	$y = -0.0282x + 3.9088$	0.3306
Loop 6 Lane 2	$y = -0.0251x + 3.8602$	0.2531

An optimal algorithm is employed to find the optimal solutions for the TPM in each group. It is worthy of mentioning that the transition probabilities are highly dependent on their initial values, since the objective function with respect to decision variables is not convex or concave over the feasible regions. After developing the TPMs, the non-homogenous Markov Chain models are used to predict the probabilities with each condition state based on the validation data set. The final results are shown in Table 6.3.

The duration model developed by Prozzi and Madanat is used to calculate the number of load repetitions to failure for the validation data set. Equation 6.7 is used to calculate PSIs. The prediction results are also shown in Table 6.3.

Finally, the developed ordered probit models and the sequential logit models using both empirical and mechanistic-empirical approaches are used as the bases for this comparison. Their proportional prediction results are also shown in Table 6.3.

As discussed in Chapter 6, the accuracy of the proportional prediction is the first comparison criterion. By examining the results of Table 6.3, it is clear that the predicted proportions of the ordered probit model and the sequential logit model and their mechanistic-empirical models are very close to the actual observed values. But the predicted values from both homogeneous and non-homogeneous Markov Chain models as well as the duration model do not match very well with the observed ones. This comparison indicates that the ordered probit model and the sequential logit model and their mechanistic-empirical models are better than the other three models.

Table 6.3 Comparison of Different Probabilistic Methods

Methodology		Very Good	Good	Fair	Poor	Very Poor
Homogeneous Markov Chain		0.0659	0.2543	0.1754	0.2415	0.2632
Non-homogeneous Markov Chain		0.0975	0.7241	0.1187	0.0279	0.0313
Duration Model		0.3368	0.1507	0.0869	0.0655	0.3600
Ordered Probit Model	**Empirical**	0.1903	0.5643	0.1874	0.0524	0.0056
	M-E	0.1900	0.5630	0.1904	0.0507	0.0058
Sequential Logit Model	**Empirical**	0.1862	0.5718	0.1876	0.0502	0.0039
	M-E	0.1898	0.5611	0.1935	0.0515	0.0038
Observed Frequency		0.1916	0.5536	0.2048	0.0437	0.0059

Note: M-E represents Mechanistic-Empirical

Another criterion for conducting the comparison is the RMSE of the expected and observed pavement conditions. By assuming the mean of each condition state as the representative value of that state, the expected value is computed using the weighted average of these condition states. All RMSEs are showed in Table 6.4. It indicates that the homogeneous Markov Chain has poor ability to predict pavement performance in this case study. Furthermore, this table also shows that the non-homogenous Markov Chain model can produce much better predictions than the homogeneous Markov Chain model. The RMSE for the duration model is 1.9643, higher than that for both the ordered probit models and the sequential logit models. The ordered probit model produces the lowest RMSE. Table 6.4 also shows that the RMSEs of the empirical and mechanistic-empirical ordered probit models are smaller than those of the sequential logit models. The reason for this result is given in Chapter 5.

Table 6.4 Comparisons of RMSE and Chi-Square

Methodology		RMSE	χ^2
Homogeneous Markov Chain		2.1300	2221.972
Non-homogeneous Markov Chain		0.6752	489.649
Duration Model		1.9643	5427.18
Ordered Probit Model	**Empirical**	0.6249	7.214
	Mechanistic-Empirical (M-E)	0.6265	4.883
Sequential Logit Model	**Empirical**	0.78339	9.191
	Mechanistic-Empirical (M-E)	0.8088	6.885

The third criterion is the chi-squared goodness-of-fit test. Given the 0.95 confidence level, the critical value of the chi-square is 9.488 with 4 degree of freedom. That is to say, the homogeneous Markov Chain, the non-homogeneous Markov Chain, and the duration model are not significant in terms of the goodness-of-fit test, while the developed ordered probit and sequential logit models are significant. Among these ordered probit and sequential logit models, the mechanistic-empirical ordered probit model has the smallest chi-square value and the chi-square value of the empirical ordered probit model is close to the chi-square value of the mechanistic-empirical sequential logit model. That indicates the sequential logit models and the ordered probit models have good goodness-of-fit, although the chi-square value of the empirical sequential logit model is relatively high. Such results are anticipated because the mechanistic-empirical ordered probit models and sequential logit models link the primary response variables with the pavement performance and furthermore the latent variables are used to represent the propensity for pavement deterioration.

6.6 Summary

This chapter presents the comparison of five probabilistic models based on a common data set. The comparison results indicate that the ordered probit models and the sequential logit models are able to yield better prediction results than the other three probabilistic models according to the comparison criteria. However, the ordered probit models and the sequential logit models are static; they cannot handle the dynamic nature of pavement deterioration. Therefore, an adaptive algorithm needs to be proposed to improve the prediction accuracy by taking new inspection data into consideration.

CHAPTER 7 ADAPTIVE PERFORMANCE MODEL

As discussed in Chapter 2, pavement deterioration is a complicated, stochastic, and dynamic process. The stochastic nature has been characterized using the probabilistic models. However, the probabilistic models cannot take the dynamic nature of pavement deterioration into consideration. This chapter is to present the methodology of a structural state space model which allows the prediction of pavement deterioration to be adaptively updated with both historical pavement performance data and new inspection data.

7.1 Model Structure of Structural State Space Model

The basic structural model was proposed in the late 1960s. This structural model was set up in terms of components which can be interpreted explicitly. The explicit model structure allows the model to directly describe the abrupt changes of the time series through a dynamic linear model representation. Generally, these abrupt changes of nonstationary processes cannot be removed by differencing or transforming the data with the Box and Jenkins time series.

The essence of the structural approach is that the observations are regarded as being made up of an underlying level component and an irregular component. The underlying level component can be further decomposed into a trend component and a seasonal component. The trend component represents the long-run movements or global trends in the series, while the seasonal component repeats itself more or less every year. For the pavement deterioration process, the seasonal pattern cannot be clearly identified in the available data sets such as the AASHO Road Test data, especially when the data is collected through accelerated testing. As a result, the seasonal component is not separately considered in this dissertation. The global trend can be represented by a perform model which is estimated with the least-square or other parameter estimation methods. On the other hand, the irregular component defined as a local trend may change its directions with time, indicating that pavement deterioration should not count only for a global trend which is defined by the regression models (Harvey, 1996). Therefore, a structural deviation is proposed to capture the discrepancy of the pavement deterioration from its global trend. Consequently, the pavement deterioration process is decomposed into three components as follows:

True Trend = Original Trend + Structural Deviations + Random Fluctuations

The original trend representing the global trend is considered as prior belief which can be obtained using the existing deterioration models. The structural deviations regarded as the local trend characterize the discrepancies based on the new available information. The random fluctuations describe the random disturbances or noise. Among these three components, how to model the structural deviations is the core of the structural model.

The structural deviations designed to capture the deviations of the pavement deterioration from the original trend can be modeled using a polynomial trend function. The polynomial trend function facilitates the formulation of a linear or quasi-linear state space form which normally consists of a transition equation and a measurement equation. Once the transition equation and measurement equation are formulated in a linear or quasi-linear state space form, various algorithms can be used to estimate the state vector, with Kalman Filter being the most popularly used algorithm. The development of the transition and measurement equations and the implementation of the Kalman Filter algorithm are further explained in the following sections.

7.2 Transition Equation

The original trend $\tilde{P}_{rt}$ of the pavement deterioration can be estimated by using the regression model based on the historical data set. For example, the original trend of the pavement deterioration process can be obtained by using the regression model based on the AASHO Road Test data. The observed trend P_{rt} of the deterioration process is modeled as a liner combination of the original trend, the structural deviation, and the random disturbance. The mathematic formula is shown in Equation 7.1:

$$P_{rt} = \tilde{P}_{rt} + \mu_t + \varepsilon_t \tag{7.1}$$

where P_{rt} is the observed trend of the deterioration process;

$\tilde{P}_{rt}$ is the original trend of the deterioration process;

μ_t is the structural deviation of the deterioration process; and

ε_t is the random disturbance.

In Equation 7.1, the random disturbance term ε_t is assumed to follow a normal distribution with zero mean. The core of developing the structural state space model is a polynomial trend model describing the structural deviations from the original trend based on following assumptions (West and Harrison, 1997):

Assumption 1 (Polynomial Trend)**:** Structural deviations at time $t+\xi$ can be represented by an m th-order polynomial function of ξ, given that the higher orders are assumed to be zero. The structural deviation from the original trend at time $t+\xi$ is represented in Equation 7.2:

$$\mu_{t+\xi} = b_0 + b_1\xi + b_2\xi^2 + \cdots + b_m\xi^m \tag{7.2}$$

where m is the maximum order of a polynomial model.

Based on the Taylor's theorem, the smooth function of $\mu_{t+\xi}$ can be expanded about the point μ_t with Equation 7.3:

$$\mu_{t+\xi} = \mu_t + \xi\mu_t^{'} + \frac{\xi^2}{2!}\mu_t^{"} + \cdots + \frac{\xi^m}{m!}\mu_t^{(m)} \tag{7.3}$$

Where $\mu_t^{'}, \mu_t^{"}, \cdots, \mu_t^{(m)}$ are the first, second, $\cdots$, and m^{th}-order derivative of the structural deviation μ_t. Comparing Equations 7.2 and 7.3, it is easy to find that the polynomial coefficient for each derivative of μ_t in the original functional form can be obtained directly by Equation 7.4:

$$b_p = \frac{\mu_t^{(p)}}{p!} \tag{7.4}$$

where p is the order of derivative for the structural deviation μ_t, normally $p \le m$.

The corresponding matrix representation for a p th-order derivative of the structural deviation μ_t can be generalized as Equation 7.5:

$$\mu_{t+\xi}^{(p)} = \sum_{s=p}^{m} \frac{\xi^{(s-p)}\mu_t^{(s)}}{(s-p)!} \tag{7.5}$$

Using Equation 7.5, a third-order polynomial trend model $\mu_{t+\xi}$ can be formulated with its third-order derivatives as Equation 7.6:

$$\begin{pmatrix} \mu_{t+\xi} \\ \mu_{t+\xi}^{'} \\ \mu_{t+\xi}^{''} \\ \mu_{t+\xi}^{'''} \end{pmatrix} = \begin{bmatrix} 1 & \xi & \frac{\xi^2}{2!} & \frac{\xi^3}{3!} \\ & 1 & \xi & \frac{\xi^2}{2!} \\ & & 1 & \xi \\ & & & 1 \end{bmatrix} \begin{pmatrix} \mu_t \\ \mu_t^{'} \\ \mu_t^{''} \\ \mu_t^{'''} \end{pmatrix} \tag{7.6}$$

Assumption 2 (Evolution Process)**:** The change of derivative μ_t can be described as Equation 7.7:

$$\mu_t^{(p)} = \sum_{s=p}^{m} \frac{\xi^{(s-p)}\mu_t^{(s)}}{(s-p)!} + w_t^{(p)} \tag{7.7}$$

where $w_t^{(p)}$ follows a normal distribution.

That is to say, the changes of the pavement performance deviations from the time interval t to $t+\xi$ are contributed by the increment due to a local Taylor series expansion term plus an evolution noise term.

Therefore, the transition equation can be represented as Equation 7.8:

$$\begin{pmatrix} \mu_{t+\xi} \\ \mu'_{t+\xi} \\ \mu''_{t+\xi} \\ \mu'''_{t+\xi} \end{pmatrix} = \begin{bmatrix} 1 & \xi & \frac{\xi^2}{2!} & \frac{\xi^3}{3!} \\ & 1 & \xi & \frac{\xi^2}{2!} \\ & & 1 & \xi \\ & & & 1 \end{bmatrix} \begin{pmatrix} \mu_t \\ \mu'_t \\ \mu''_t \\ \mu'''_t \end{pmatrix} + \begin{pmatrix} w_t \\ w'_t \\ w''_t \\ w'''_t \end{pmatrix} \tag{7.8}$$

The complete transition equation can be written as Equation 7.9:

$$\boldsymbol{x}_{t+1} = \boldsymbol{A}_t \boldsymbol{x}_t + \boldsymbol{w}_t \tag{7.9}$$

where $\boldsymbol{x}_t = (\mu_t, \mu'_t, \mu''_t, \mu'''_t)'$ and $\boldsymbol{w}_t = (w_t, w'_t, w''_t, w'''_t)'$

In order to obtain the prediction of performance at time $t+\xi$, the structural deviation must be calculated based on the information at the current time. Then, the original trend of the polynomial deterioration can be substituted into the initial model structure according to Equation 7.10:

$$E[P_{rt+\xi} \mid \mu_t] = \tilde{P}^r{}_{rt+\xi} + E[\mu_{t+\xi} \mid \mu_t] = \tilde{P}^r_{rt+\xi} + \sum_{s=0}^{m} \frac{\xi^s}{s!} \hat{\mu}_t^{(s)} \tag{7.10}$$

It is important to point out that, during this process, the reliable estimate of the original deterioration trend is also important, because the structural deviations are defined as the deviations from the original deterioration trend.

7.3 Measurement Equation

The measurement equation is used to represent the relationship between observed variables and the defined states. The measured variables can be represented by Equation 7.11:

$$MP_t = P_{rt} + v_t \tag{7.11}$$

where v_t is the measurement noise with normal distribution of zero mean;

MP_t is the measured trend value of the pavement deterioration process.

Relating the measurements to the state variables defined previously, Equation 7.11 is rewritten as Equation 7.12:

$$MP_t = \widetilde{P}^{r}_{rt+\xi} + \sum_{s=0}^{m} \frac{\xi^s}{s!} \hat{\mu}_t^{(s)} + \varepsilon_t + v_t \tag{7.12}$$

It can be further transformed as Equation 7.13:

$$MP_t - \widetilde{P}^{r}_{rt+\xi} = \sum_{s=0}^{m} \frac{\xi^s}{s!} \hat{\mu}_t^{(s)} + \varepsilon_t + v_t \tag{7.13}$$

Then, the measurement equation can be written as Equation 7.14:

$$\boldsymbol{z}_t = \boldsymbol{H}_t \boldsymbol{x}_t + \boldsymbol{v}_t \tag{7.14}$$

where $\boldsymbol{z}_t = MP_t - \widetilde{P}^{r}_{rt+\xi}$;

$\boldsymbol{v}_t = \varepsilon_t + v_t$;

$\boldsymbol{H}_t$ is $\left(1, \quad \xi, \quad \cdots, \quad \frac{\xi^m}{m!}\right)$.

In the above equations, the final measurement error combines the random noise and the measurement error.

7.4 Kalman Filter Estimation

Once the linear or quasi-linear state space model is developed, the Kalman Filter algorithm is used to estimate its state vector. The Kalman Filter algorithm proposed by Rudolf Kalman in 1960 is a recursive procedure of optimally estimating the state vector based on available information at time t. The Kalman Filter estimation process is analogous to the process of the feedback control in the sense that the filter estimates the state vector at time t and then obtains the feedback based on noise measurements. The feedback process is also known as a predict-correct process, consisting of the measurement update equations called "predict" and the time update equations called "correct". The time update equations are responsible for propagating the current state and error covariance to attain the prior estimates in the next time step. The measurement update equations are responsible for improving a posteriori estimate by incorporating a new measurement into the prior estimate. The Kalman Filter estimation process is shown in Figure 7.1 (Welch and Bishop, 2004).

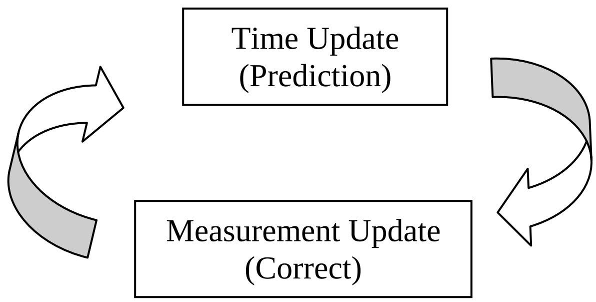

Figure 7.1 Kalman Filter Estimation Algorithm Flowchart

The assumption for the Kalman Filter estimation algorithm is that $\boldsymbol{v}_t$ and $\boldsymbol{w}_t$ are uncorrelated white noises following normal distributions: $\boldsymbol{v}_t \sim N(0, \boldsymbol{V}_t)$ and $\boldsymbol{w}_t \sim N(0, \boldsymbol{W}_t)$, where $\boldsymbol{V}_t$ and $\boldsymbol{W}_t$ are covariance matrices of measurement noise and process noise respectively. The Kalman Filter algorithm is used to estimate the states. The Kalman Filter estimation algorithm is based on the Bayes' rule where prior estimate $\hat{\boldsymbol{x}}_t$ is related to prior measurement $\boldsymbol{z}_t$ in terms of minimizing estimation errors. During this process, the estimated state error covariance is defined by $\boldsymbol{Q}_t$ as $\boldsymbol{Q}_t = E[(\boldsymbol{x}_t - \hat{\boldsymbol{x}}_t)(\boldsymbol{x}_t - \hat{\boldsymbol{x}}_t)']$. The detailed Kalman Filter algorithm is illustrated as follows (Ljung and Soderstrom, 1983):

Step 1: (Initialization) Set up initial estimates of $\boldsymbol{Q}_0$ and $\boldsymbol{x}_0$.

Step 2: (Time Update Equations) Propagate the means and covariance estimates from state t to $t+\xi$:

$$\hat{\boldsymbol{x}}_{t+\xi} = \boldsymbol{A}_t \boldsymbol{x}_t \tag{7.15}$$

$$\boldsymbol{Q}_{t+\xi} = \boldsymbol{A}\,\boldsymbol{Q}\,\boldsymbol{A}_{\boldsymbol{t}}^{'} + \boldsymbol{W} \tag{7.16}$$

Step 3: (Measurement Update Equations) After receiving the new measurement, the weighting function is updated as:

$$\boldsymbol{K}_{t+\xi} = \boldsymbol{Q}_{t+\xi}\boldsymbol{H}_{\boldsymbol{t}}^{'}(\boldsymbol{H}_{t}\boldsymbol{Q}_{t+\xi}\boldsymbol{H}_{\boldsymbol{t}}^{'} + \boldsymbol{V}_{t})^{-1} \tag{7.17}$$

The posterior means and covariance are updated as:

$$\boldsymbol{x}_{t+\xi} = \boldsymbol{x}_{t+\xi} + \boldsymbol{K}_{t+\xi}(\boldsymbol{z}_{t} + \boldsymbol{H}_{t}\boldsymbol{x}_{t}) \tag{7.18}$$

$$\boldsymbol{Q}_{t+\xi} = (\boldsymbol{I} - \boldsymbol{K}_{t}\boldsymbol{H}_{t})\boldsymbol{Q}_{t} \tag{7.19}$$

where $\boldsymbol{I}$ is an identity matrix.

Step 4: (Estimation of the New State Variables) Calculate the new estimate for the state of the pavement deterioration processes based on the new estimation.

$$P_{rt+\xi} = E[\tilde{P}^{r}_{rt+\xi} + \mu_{t+\xi} + \varepsilon_{t}] = \tilde{P}^{r}_{rt+\xi} + \hat{\mu}_{t+\xi} \tag{7.20}$$

In this case, the proposed algorithm only requires prior mean and covariance statistics other than the historical data series. This makes the computation more efficient, especially when prediction intervals are short.

During this process, one issue that deserves special attention is the selection of the order of the polynomial trend model. Generally, a smooth curve requires the lower order, although the higher order of the polynomial trend models are recommended in order to capture the non-linearity in the structural changes. In practice, the order of the polynomial trend models is rarely found to be higher than three (West and Harrison, 1997). In order to evaluate the accuracy of the predictions from polynomial trend models, the RMSE is used as a quantitative criterion for the predicted values in Equation 7.21.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T}(P_{rt} - MP_t)^2}{T}} \tag{7.21}$$

where t is the index for the observation time interval, $t = 1,2,\cdots,T$.

7.5 Summary

This chapter presents the theoretical background of the adaptive algorithm. The proposed method decomposes the dynamic processes into three components: the original trend, structural deviation, and the random fluctuation. The polynomial trend models are proposed to approximate the structural deviations from the original trend. After formulating a linear state space model, the Kalman Filter algorithm is employed to estimate the condition states of the deterioration process. During that process, the proposed method can be easily integrated with the current pavement performance regression models under a coherent framework. In order to know whether the proposed methodology is applicable or not, a case study using the real data needs to be conducted.

CHAPTER 8 CASE STUDY OF ADAPTIVE PERFORMANCE MODEL

The methodology of the adaptive algorithm has been presented in the last chapter. The proposed model employs a polynomial trend filter to recursively estimate and predicts the possible structural deviations from the prior estimated original trend of the pavement deterioration by means of the Kalman Filter algorithm. In order to evaluate the feasibility and robustness of the proposed method, a case study is conducted to demonstrate its applicability. The details of the case study are discussed in this chapter.

8.1 Simulated Data

The proposed state space model presented in Chapter 7 is used for adaptively modeling the process of pavement deterioration. The proposed model is expected to be robust under disruptions caused by special events such as maintenance actions and environmental factors. In order to demonstrate the feasibility of the proposed methodology, simulation experiments were conducted to illustrate the application of the developed methodology to the prediction of the pavement performance.

The data set used to conduct the analysis consists of the historical data set and the simulated data set. The elements of the combined data set are illustrated in Figure

8.1. The historical data is the AASHO Road Test data collected during the AASHO Road Test. The AASHO Road Test data was used to calculate the original trend of the structural state space model. To be more specific, the utility function of the ordered probit model developed in Chapter 5 was used to calculate the original trend. The developed relationship is shown in Equation 8.1.

$$U_n = 1.19379 - 0.10967 D_s - 0.01859 D_b + 3.00657 \times 10^{-7} T_{ESAL} + 0.05729 S \quad (8.1)$$

Based on the developed utility function, individual probability with which the pavement would fall into each condition state was calculated. For example, the probability for the condition state "Good" can be calculated by using Equation 8.2, where Φ is the standard normal cumulative distribution.

$$\begin{aligned} P(C_n = 1) = \Phi[1.67585 - (1.19379 - 0.10967 D_s - 0.01859 D_b + \\ 3.00657 \times 10^{-7} T_{ESAL} + 0.05729 S)] - \Phi(1.19379 \\ - 0.10967 D_s - 0.01859 D_b + 3.00657 \times 10^{-7} T_{ESAL} + 0.05729 S) \end{aligned} \quad (8.2)$$

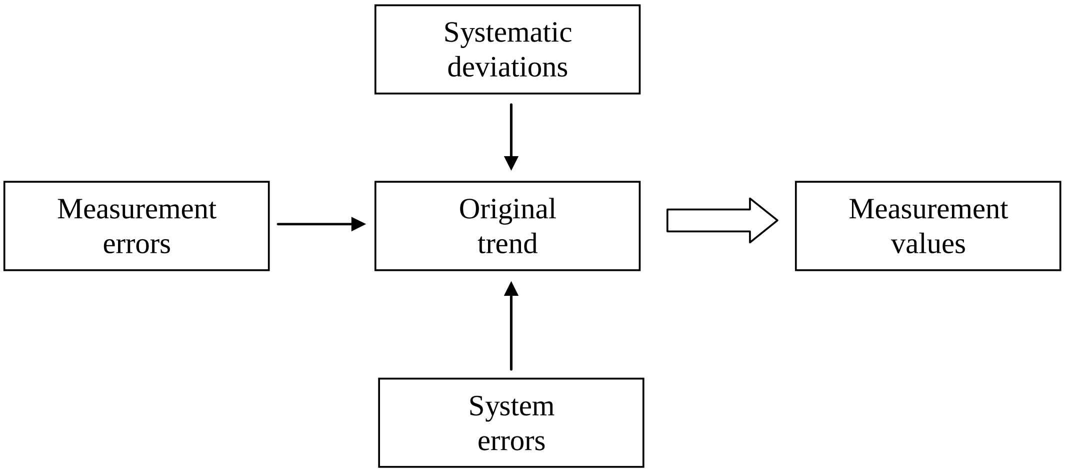

Figure 8.1 Illustration of Data Composition

The original trend $\tilde{P}_{rt}$ for each condition state was obtained by aggregating the individual probability P_n together at each inspection time point. Among those five state probability curves, the probability curve of condition state 2 representing the "Good" pavement condition was selected to illustrate the feasibility of the developed method. The calculated original trend is illustrated in Figure 8.2.

If there are no abrupt changes or measurement errors, the ordered probit model is sufficient to provide an accurate estimation of future pavement deterioration. However, if some abrupt changes caused by the environmental factors or unobserved factors occur, the non-adaptive model may not be able to effectively reflect these changes. In this case, the structural state space model can be employed to address the abrupt changes by considering them as structural deviations. Given that the ordered probit model is used to define the original trend $\tilde{P}_{rt}$, the proposed structural state space model should be implemented to update the changes of the probabilities in the "Good" condition state. Once the original trend $\tilde{P}_{rt}$ is established, the structural deviations μ_t can be approximated by a polynomial trend model. The observed trend P_{rt} of the pavement deterioration process is modeled by a linear combination of the original trend, the structural deviation, and the random disturbance shown in Equation 7.1.

Another data set used in this case study is the simulated data for testing the validity of the models. The reason for using a simulated data set is that the measurement variances in the proposed state space model cannot be accurately obtained from the AASHO Road Test data. During the AASHO Road Test, some measurements were made by people based on their subjective judgments. For instance, the PSI was based on the perception of road users about the ride quality of the pavement sections (Huang, 1993). Although the relationship between the PSIs and the objective measurements was developed by using regression analysis, it is still difficult to clearly define the statistical characteristics of the measurement errors, which could mislead the assessment of the effectiveness and robustness of the proposed structural state space model. Moreover, the system variance is also difficult to directly quantify. However, with simulated data, where measurement and system errors can be precisely controlled, the effectiveness of the proposed algorithm can be effectively tested.

Once the original trend $\tilde{P}_{rt}$ for "Good" condition state is determined, the simulation method can be implemented to generate the random measurement errors with predefined distribution parameters. The measurements used for testing the structural state space model are created by combining the original trend obtained from the AASHO Road Test data and simulated measurement and system errors. With the obtained measurements of probability changes in the "Good" condition state, the structural state space model can be applied to estimate these changes by employing a transition equation, a measurement equation, and the Kalman Filter algorithm.

8.2 Scenario Analyses

In order to take different phenomena of pavement deterioration into account, three scenarios were designed to illustrate the feasibility and robustness of the proposed method: 1) estimate the condition states when the controlled measurement errors are inherent in the deterioration process; 2) estimate the condition states when the deterioration process has systematic mean deviations but without measurement errors; and 3) estimate the condition states when the deterioration process is embedded with both systematic mean deviations and random measurement errors. The three scenarios are shown in Table 8.1.

Table 8.1 Demonstration of Predefined Three Scenarios

Scenarios	Systematic Mean Deviations	Measurement Errors
Scenario I		X
Scenario II	X	
Scenario III	X	X

8.2.1 Scenario I

For the first scenario, the proposed approach is to estimate the condition states when the deterioration process is embedded only with random measurement errors. As explained in the previous section, data used in this scenario is the simulated data obtained by employing a data simulator to generate measurement errors normally distributed with a mean of zero and different levels of standard deviations. The measurements are then obtained by combining the original trend and the simulated measurement errors. Once those measurements are generated, the structural state space model is implemented to predict the probability of state 2 in which the predictions are set to start from index day 37.

Figure 8.2 and Figure 8.3 demonstrate the probabilities predicted by the polynomial trend models with measurement errors defined by the normal distributions with standard deviation of 0.2 and 0.05 respectively.

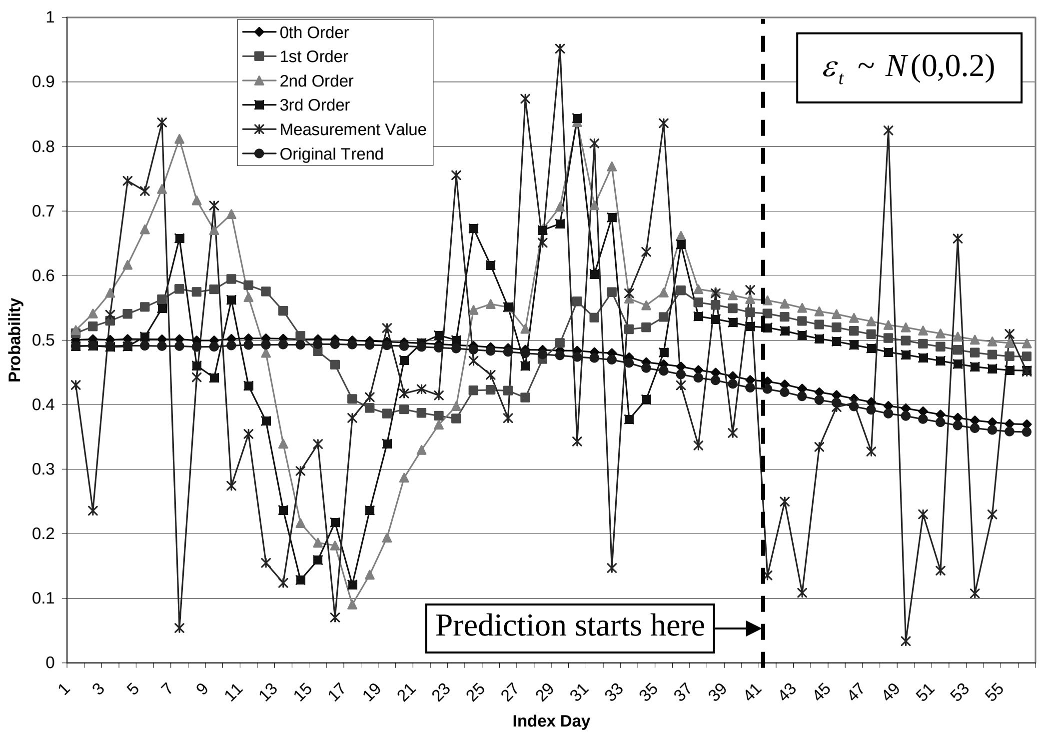

Figure 8.2 Comparison of Predictions for Data Embedded with Normally Distributed Random Errors Defined by $\varepsilon_t \sim N(0, 0.20)$

By comparing Figure 8.2 and Figure 8.3, it is not difficult to see that smaller standard deviations of the measurement errors make the predicted values closer to the measured values than to the original trend, showing the property of the Kalman Filter algorithm. That is to say, when the standard deviation of the measurement errors is large, the Kalman Filter algorithm tends to weight more on the prior estimation than when the standard deviations of measurement errors are small before it approaches to the steady state. In addition, when the 0^{th}-order is employed in the polynomial trend model, the state space model is equal to the random walk plus noise.

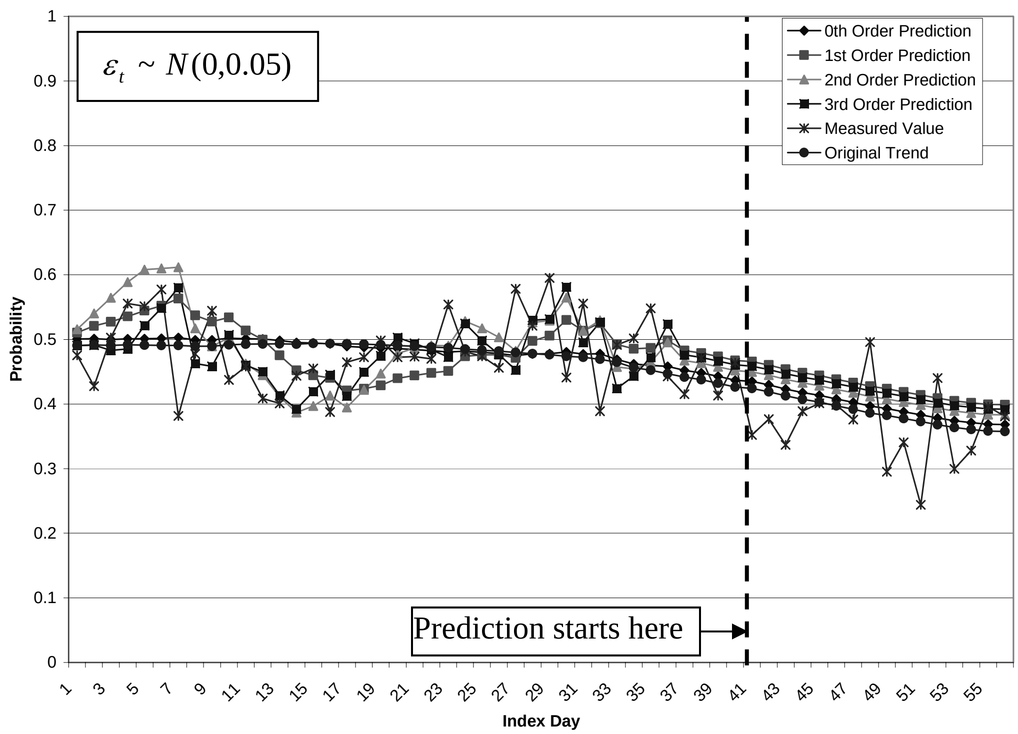

Figure 8.3 Comparison of Predictions for Data Embedded with Normally Distributed Random Errors Defined by $\varepsilon_t \sim N(0, 0.05)$

8.2.2 Scenario II

For the second scenario, the simulated data is designed to represent a significant shift between the observed trend and the original trend, aiming at examining the ability of the proposed approach to identify the abrupt system deviations. In this scenario, only the abrupt upward or downward deviations are presented. To be more specific, a 0.1 upward deviation of the probability curve was imposed on index day 11. Then, a 0.15 downward deviation was observed on index day 21. Similar to the first scenario, the predictions were also set to start from index day 37. The prediction results are illustrated in Figure 8.4.

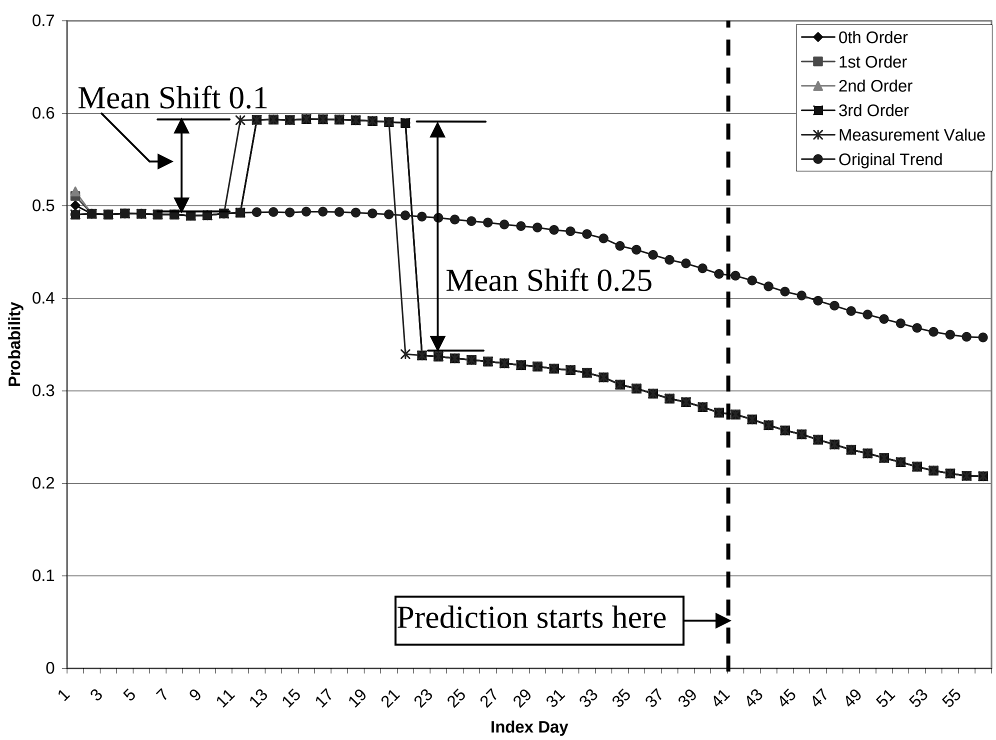

Figure 8.4 Comparison of Predictions for Data without Random Errors but with Systematical Mean Shifts

Figure 8.4 shows that the proposed model can adaptively identify the mean deviations of the probability curve when such deviations occur. In addition, the prediction results are fairly close to the measured values.

8.2.3 Scenario III

The third scenario is the extension of the second scenario. The simulated data was generated by combining random measurement errors and the systematic derivations which have been created in the first and second scenarios. The purpose of designing this scenario is to investigate the ability of the developed approach to recognize the systematic mean derivations from the random measurement errors. Figure 8.5 shows the estimation results where predictions were made from index day 37.

By examining Figure 8.5, it is clear that the structural state space model can effectively differentiate the abrupt upward and downward mean changes from the measurement errors. In contrast, the regression predictions without adaptive update still yield fixed prediction values which are significantly different from the real deterioration process.

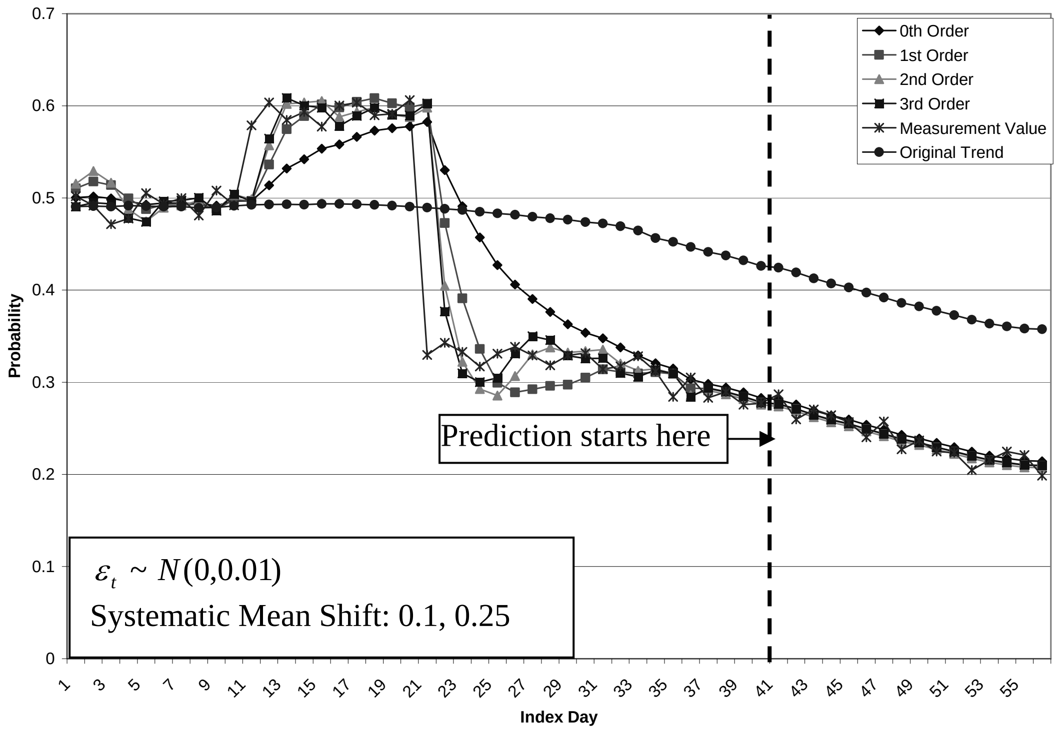

Figure 8.5 Comparison of Predictions for Data with Random Errors ε_t and Systematical Mean Shifts

In order to compare the prediction accuracy of the proposed structural state space model with the original trend curve, the RMSEs from the structural state space models and the regression estimation are presented in Figure 8.6. Figure 8.6 shows that the state space model can yield better predictions than the prior original trend estimation. In Figure 8.6, the largest prediction errors occur on index days 10 and 20. The relatively large errors are caused by the lagged responses of the model and the abrupt system deviations. After each abrupt point, the structural state space model can adaptively adjust itself to yield better predictions.

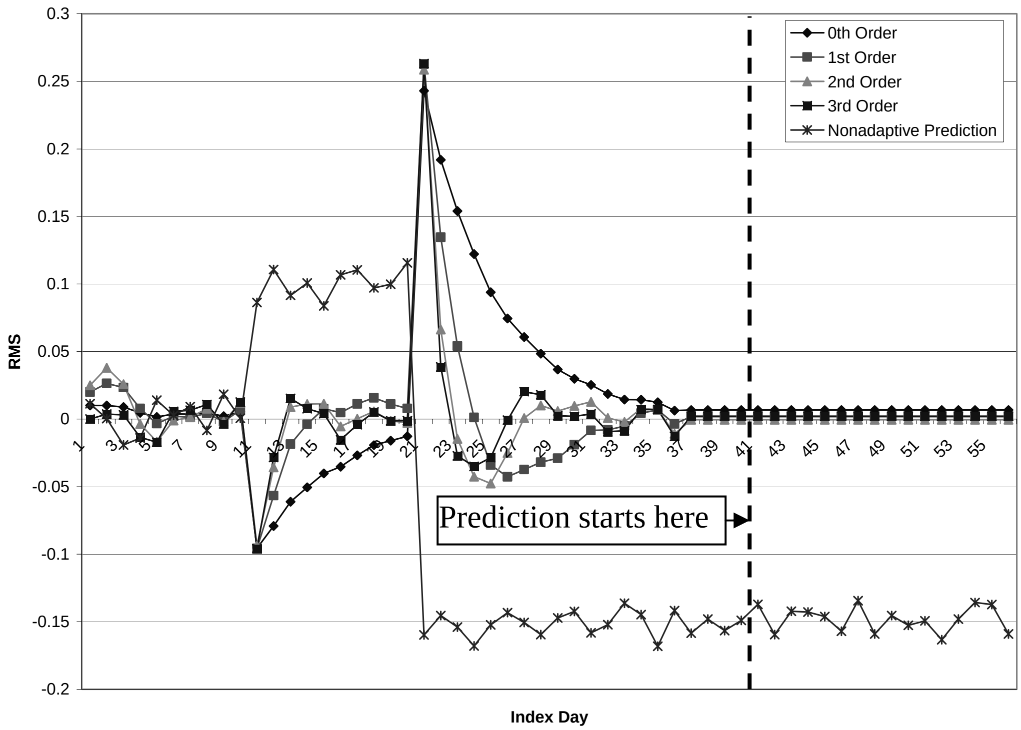

Figure 8.6 RMSE Comparison between Structural State Space Predictions and Non-Adaptive Predictions

In order to quantify the effects of the order on the polynomial trend models, the RMSEs are presented in Table 8.2. In terms of the RMSEs, the accuracy of the prediction is acceptable for all models, since the largest RMSE corresponding to the polynomial trend models is only 0.07087. Table 8.2 also indicates that the non-adaptive model has much larger RMSEs than the adaptive models in scenario II and III, although it has relatively smaller RMSEs than the adaptive models in scenario I. Additionally, in the random measurement error situation, the lower order polynomial model is better than the higher order model. However, in the mean-shift scenario, the higher order polynomial model is better than the lower order one. If real-time information is available, higher order polynomial trend models are always recommended in order to capture the possible structural deviations (Zhou and Mahmassani, 2004). Therefore, it is not concluded that the higher order of the polynomial function can produce better predictions. The selection of the order is depended on the characteristics of the available data and engineers' judgments. Table 8.2 also indicates that the differences among different polynomial trend models are very small. Such small differences imply that a low order polynomial trend model is acceptable for this case study.

Table 8.2 RMSE Comparisons of the Four Polynomial Trend Models

Scenarios	**0^{th}-order**	**1^{st} -order**	**2^{nd} -order**	**3^{rd} -order**	**Non-adaptive Prediction**
Scenario I $\varepsilon_t \sim N(0,0.05)$	0.06107	0.07094	0.07002	0.07087	0.05916
Scenario II	0.03601	0.03608	0.03614	0.03598	0.12748
Scenario III	0.05764	0.04475	0.04021	0.03925	0.12798

In summary, the three scenarios represent three possible situations in the pavement deterioration process. The prediction results for the three scenarios indicate that the proposed state space model is capable of capturing the time-varying trends of the deterioration process to give better predictions.

8.3 Summary

This chapter presents a structural state space model to adaptively model the dynamic characteristics of pavement deterioration processes. The case study indicates that the structural state space model can provide effective and robust predictions for both the deterioration processes associated with random measurement errors and those with significant structural changes. Based on the RMSEs, the proposed structural model yields better predictions than the prior regression model. In addition, the proposed method can be easily integrated with any existing infrastructure deterioration models. Given these preliminary results, it can be concluded that the structural state space model is effective and robust for describing the dynamic process of pavement deterioration.

CHAPTER 9 SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

This chapter briefly summarizes the research process and findings. Then, major conclusions are presented. Recommendations for future research are also included in this chapter.

9.1 Summary

The purpose of this research is to develop a comprehensive framework for modeling the deterioration process of pavements, in order to assist engineers and administrators in effectively managing pavements through better performance prediction. As discussed in Chapter 2, most of previous work in pavement performance models are either limited by their inadequate consideration of the stochastic nature of pavement deterioration or restricted by complications arising from the non-homogeneous assumptions, especially for Markov Chain models. In addition, most of previously developed models are static and unable to update the parameters of the developed pavement deterioration models when newly collected data is available. This research is aimed at capturing the stochastic and dynamic nature of pavement deterioration by overcoming these shortcomings of previously developed models.

Under this comprehensive framework, the ordered probit models and the sequential logit models are developed, calibrated, and validated using the AASHO Road Test data. Then an adaptive method is proposed to improve the prediction accuracy of pavement performance by taking newly inspected data into consideration, where a structural state space model is employed to identify any structural deviations which are then approximated with a polynomial trend function. This proposed state space model structure has the ability to integrate the developed probabilistic models with the structural deviations. The case study results based on the simulated data confirm the effectiveness and robustness of the structural state space model.

9.2 Conclusions

Conclusions drawn from this study are as follows:

1) The stochastic and dynamic nature of pavement deterioration processes can be effectively characterized with an integrated framework of probabilistic and adaptive models. The proposed framework can also be expanded to model the deterioration of other civil infrastructure systems;

2) Based on the validation results, it is clear that the ordered probit models and sequential logit models are able to directly predict the probabilities of pavement condition states and characterize the stochastic nature of pavement performance. With the proposed methodologies, uncertainties of pavement performance are also captured by linking the causal variables with the pavement condition states. More importantly, the developed models are able to yield good predictions without the time-consuming

process of developing the transition probability matrixes, especially for the nonstationary deterioration processes.

3) The developed mechanistic-empirical models incorporate the primary response variables into the model specifications, extending the inference space of the pavement performance models beyond the original range of the AASHO Road Test data.

4) The proposed adaptive method employs a state space model format to characterize the structural deviations from the original trend predicted from the proposed probabilistic models and estimates the parameters of the state space model using the Kalman Filter algorithm. The results of the case study indicate that the proposed adaptive algorithm is effective and robust for updating the developed probabilistic models with new observations under most of the pavement deterioration scenarios.

5) Although the methodological framework is developed and tested for pavement deterioration, it can be implemented and extended to describe the performance of other transportation infrastructure facilities.

9.3 Recommendations for Future Research

The proposed methods capture the stochastic and dynamic nature of pavement deterioration and have the ability to better predict the pavement performance compared with other methods, but some limitations still exist and should be further researched. Key recommendations for future research are discussed as follows:

1) The data source used in this dissertation is the AASHO Road Test data which does not include any information on the impact of maintenance and rehabilitation actions, as no major maintenance and rehabilitation was applied during the testing period. Although the mechanistic-empirical method is used to link the primary responses with the pavement performance to increase the inference space of the AASHO Road Test, the impact of maintenance and rehabilitation actions needs to be further studied with a data set including maintenance and rehabilitation effects on pavement sections. Furthermore, more explanatory variables, such as temperature and moisture, need to be included in the probabilistic model structure, if the proposed methodologies are applied to in-service pavement data sets because of their uncontrollability and variability.

2) For the adaptive part, a case study using a real data set needs to be conducted to further evaluate its stability and robustness. The parameters of the original trend developed from the historical data can also be updated to better explain the underlying reasons of the complicated deterioration processes. In addition, the proposed adaptive algorithm is only based on the linear assumption. The extended Kalman Filter or the neural network can be employed to further analyze nonlinear situations.

3) Finally, the current probabilistic models are a linear combination of explanatory variables. This combination is not based on the physical principles of pavement deterioration. As a result, the model structure cannot avoid limitations arising from its specification form. The model specification form needs to be further studied based on physical principles using certain methods such as experimentation or

dimensional analysis. The dimensional analysis method can identify a minimal set of parameters and their relationships using the dimensionless groups, making engineers better visualize the deterioration processes. In addition, the dimensionless groups can also reflect the physical similarity if they are constant.

BIBLIOGRAPHY

[AASHO, 1962] American Association of State Highways Officials, AASHO, *The AASHO Road Test Report 5, Pavement Research*. Special Report 61 E. HRB, National Research Council, Washington, D.C., 1962.

[AASHTO, 1993] American Association of State Highways and Transportation Officials, AASHTO, *AASHTO Guide for Design of Pavement Structures*. AASHTO, Washington, D.C., 1993.

[Amemiya, 1975] Amemiya, T., "Qualitative Response Models," *Annals of Economic and Social Measurement*, 1975, 4(3), pp. 363-372.

[Archilla, 2000] Archilla, A. R. and S. Madanat, "Development of A pavement Rutting Model from Experimental Data," *Journal of Transportation Engineering*, 2000, 126(4), pp.291-299.

[Ashok, 2000] Ashok, K. and M. Ben-Akiva, "Alternative Approaches for Real-Time Estimation and Prediction of Time-Dependent Origin-Destination Flows," *Transportation Science*, 2000, 34(1), pp.21-36.

[Ben-Akiva, 1985] Ben-Akiva, M. and S. R. Lerman, *Discrete Choice Analysis: Theory and Application to Travel Demand*, 1985, The MIT Press, Cambridge, Massachusetts, London, England.

[Bernardo, 1994] Bernardo, J. M. and A. F. M. Smith, *Bayesian Theory, Wiley*

Series in Probability and Mathematical Statistics, 1994, John Wiley & Sons Ltd.

[Bhat, 1998] Bhat, C. R. and V. Pulugurta, "A Comparison of Two Alternative Behavioral Choice Mechanisms for Household Auto Ownership Decisions", *Transportation Research Part B*, 1998, 32(1), pp.61-75.

[Box, 1976] Box, G. E. P. and G. M. Jenkins, *Time Series Analysis Forecasting and Control*, 1976, Holden-Day Inc., San Francisco.

[Bourdeau, 1990] Bourdeau, P. L., "Probabilistic Modeling of Flexible Pavements," *Transportation Research Record*, No. 1286, 1990, pp. 184-191.

[Butt, 1987] Butt, A. A., M. Y. Shahin, K. J. Feighan, and S. H. Carpenter, "Pavement Performance Prediction Model Using the Markov Process," *Transportation Research Record*, No. *1123*, 1987, pp.12-19.

[CSI, 2002] Cambridge Systematics, Inc., *Transportation Asset Management Guide*, National Cooperative Highway Research Program (NCHRP) Project 20-24(11), 2002.

[Carnahan, 1988] Carnahan, J. V., "Analytical Framework for Optimizing Pavement Maintenance," *Journal of Transportation Engineering*, 1988, 114(3), pp. 307-322.

[Cary, 1960] Cary, W. N. and P. E. Irick, "The Pavement Serviceability Performance Concept," *Bulletin 250, Highway Research Board*, 1960.

[Cheetham, 1998] Cheetham, A., “Auto-Adaptive Pavement Performance Predication Methodology,” *Fourth International Conference on Managing Pavement*, 1998, 2, pp.552-567.

[Chu, 2002] Chu, Y., “Automobile Ownership Analysis Using Ordered Probit Models,” *Transportation Research Record*, No. 1805, Transportation Research Board, Washington, D.C. 2002, pp.60-67.

[Cox, 1972] Cox, D. R., “Regression Models and Life Tables,” *Journal of Statistical Society*, 1972, B26, pp.186-220.

[Cragg, 1970] Cragg, J. G. and R. Uhler, “The Demand of Automobiles,” *Canadian Journal of Economics:* 1970, 3, pp.386-406.

[Damnjanovic, 2005] Damnjanovic, I. and Z. Zhang, “Applying Method of Moments for Development of Pavement Reliability Function”, *Proceedings of 84th Annual Meeting of the Transportation Research* Board *(CD-Rom),* Transportation Research Board: Washington, D. C. 2005.

[DeStefano, 1998] DeStefano, P. D., and D. Grivas, “A Method for Estimating Transition Probability in Bridge Deterioration Models,” *Journal of Infrastructure Systems*, ASCE, 1998, 4(2), pp.56-62.

[Durango, 2002] Durango, P. L., *Adaptive Optimization Models for Infrastructure Management*, 2002, The university of California, Berkeley, Dissertation.

[Durango, 2002] Durango-Cohen, P. and S. Madanat, "Optimal Maintenance and Repair Policies in Infrastructure Management under Uncertain Facility Deterioration Rates: An Adaptive Control Approach," *Transportation Research Part A*, 2002, 36(9), pp. 763-778.

[Easa, 1996] Easa, S. M., A. Shalaby, and A. O. A. E. Halim, "Reliability-Based Model for Predicting Pavement Thermal Cracking," *Journal of Transportation Engineering*, Sept. and Oct., 1996, pp. 374-380.

[FHWA, 2002] FHWA, http://www.fhwa.dot.gov/tea21/teafunds.htm, visited February, 2002.

[FHWA, 1998] FHWA, Pavement Preservation: A Road Map for the Future, 1998.

[Garcia-Diaz, 1984] Garcia-Diaz, A. and M. Riggins, "Serviceability and Distress Methodology for Predicting Pavement Performance," *Transportation Research Record*, No. 997, 1984, pp.56-61.

[George, 1986] George, K. P. and S. Husain, "Thickness Design for Flexible Pavement: A Probabilistic Approach," *Transportation Research Record*, No. 1095, 1986, pp. 26-36.

[Gharaibeh, 2002] Gharaibeh, N. G. and M. I. Darter, "Probabilistic Analysis of Highway Pavement Life for Illinois," *Transportation Research Record*, No. 1823, 2002, pp.111-120.

[Golabi, 1982] Golabi, K., R.B. Kulkarni, and G. B. Way, "A Statewide Pavement Management System," *Interfaces 12*: 6, 1982, pp.5-21.

[Grau, 1993] Grau, R. W., *Geotechnical Laboratory, Effects of Variable Tire Pressure on Road Surfacings, Volume 1: Design, Construction, Behavior under Traffic, and Test Results,* Technical Report GL-93-20, August 1993.

[Haas, 1994] Haas, R., W. R. Hudson, and J. Zniewski, *Modern Pavement Management*, Krieger Publishing Company, Malabar, Florida, 1994.

[Hajek, 1996] Hajek, J. J. and A. Bradbury, "Pavement Performance Modeling Using Canadian Strategic Highway Research Program Bayesian Statistical Methodology," *Transportation Research Record*, No. 1524, 1996, pp.160-170.

[Harvey, 1996] Harvey, A. C., *Forecasting, Structural Time Series Models and the Kalman Filter*, 1996, Cambridge University Press.

[HRB, 1972] Highway Research Board, *National Cooperative Highway Research Program Synthesis of Highway Practice 14: Skid Resistance*. Highway Research Board, National Academy of Sciences, Washington, D.C. 1972.

[Horowitz, 1982] Horowitz, J. L., "Evaluation of Usefulness of Two Standard Goodness-of-Fit Indicators for Comparing Non-Nested Random

Utility Models," *Transportation Research Record*, No. 874, Transportation Research Board, Washington, D.C. 1982, pp.19-25.

[Huang, 1993] Huang, Y. H., *Pavement Analysis and Design*, 1993, Prentice-Hall, Inc.

[Humplick, 1992] Humplick, F., "Highway Pavement Distress Evaluation: Modeling Measurement Error," *Transportation Research Part B*, 1992, 26(2), pp.135-154.

[Irick, 1991] Irick, Paul E., Stephen B. Seeds, and M. A. Diaz, *Characteristics of Load Equivalence Relationships Associated with Pavement Distress and Performance,* Phase II Final Report, for Trucking Research Institute, ATA Foundation, Inc., November 1991.

[ISTEA, 1991] *Intermodal Surface Transportation Efficiency Act*, http://ntl.bts.gov/DOCS/ste.html, 1991.

[Jiang, 1989] Jiang, Y., M. Saito, and K. C. Sinha, "Bridge Performance Prediction Model Using the Markov Chain," *Transportation* Research *Record*, No. 1180, Transportation Research Board, Washington, D.C. 1989, pp.25-32.

[Kahn, 1979] Kahn, L. M., and Morimune, K., "Unions and Employment Stability: A Sequential Logit Approach," *International Economic Review*, 1979, 20(1), pp. 217-235.

[Kawa, 2000] Kawa, I., *Evaluation and Extension of the AASHTO LEFs for*

Changing Traffic Characteristics, Ph. D dissertation, 2000, the University of Texas at Austin.

[Kulkarni, 1984] Kulkarni, R., “Dynamic Decision Model for a Pavement Management System,” *Transportation Research Record*, No. 997, 1984, pp.11-19.

[Kumar, 1994] Kumar, D. and B. Klefsjo, “Proportional Hazards Model: A Review,” *Reliability Engineering and System Safety* 44, 1994, pp. 177-188.

[Li, 1996] Li, N, W. Xie, and R. Haas, “Reliability-Based Processing of Markov Chains for Modeling Pavement Deterioration,” *Transportation Research Record*, No. 1524, 1996, pp.203-213.

[Lister, 1967] Lister, N.W. and R. Jones, “The Behavior of Flexible Pavements Under Moving Wheel Loads,” *Proceedings*, *Second International Conference on the Structural Design of Asphalt Pavements*, University of Michigan, Ann Arbor, 1967.

[Ljung, 1983] Ljung, L. and T. Soderstrom, *Theory and Practice of Recursive Identification,* 1983, MIT Press, Cambridge, Massachusetts London, England.

[Lu, 1992] Lu, J., C. Bertrand, W. R. Hudson, and B.F. McCullough, “Adaptive Filter Forecasting System for Pavement Roughness,” *Transportation Research Record*, No.1344, 1992, pp.124-129.

[Lu, 1994] Lu, Y. and S. Madanat, “Bayesian Updating of Infrastructure

Deterioration Models," *Transportation Research Record*, No.1442, 1994, pp.110-114.

[Madanat, 1993] Madanat, S., "Optimal Infrastructure Management Decisions under Uncertainty," *Transportation Research Part C*, 1993, 1(1), pp.77-88.

[Madanat, 1995] Madanat, S., S. Bulusu, and A. Mahmoud, "Estimation of Infrastructure Distress Initiation and Progression Models," *Journal of Infrastructure Systems*, 1995, 1(3), pp.146-150.

[Madanat, 1993] Madanat, S. M., "Incorporating Inspection Decisions in Pavement Management," *Transportation Research Part B*, 1993, 27(6), pp. 425-438.

[Madanat, 1997] Madanat, S., Karlaftis, M.G., and P. S. McCarthy, "Probabilistic Infrastructure Deterioration Models with Panel Data," *Journal of Infrastructure Systems*, 1997, 3(1), pp.4-9.

[Madanat, 2002] Madanat, S., J. A. Prozzi, and M. Han, "Effect of Performance Model Accuracy on Optimal Pavement Design," *Computer-aided Civil and Infrastructure Engineering*, 2002, 17(1), pp. 22-30.

[Madanat, 1995] Madanat, S., S. Bulusu, and A. Mahmoud, "Estimation of Infrastructure Distress Initiation and Progression Models," *Journal of Infrastructure Systems*, 1995, 1(3), pp.146-150.

[Madanat, 1997] Madanat, S., M. G. Karlaftis, and P. S. McCarthy, "Probabilistic Infrastructure Deterioration Models with Panel Data," *Journal of*

Infrastructure Systems, 1997, 3(1), pp. 4-9.

[Madanat, 1995] Madanat, S., R. Mishalani, and W. H. W. Ibrahim, “Estimation of Infrastructure Transition Probabilities from Condition Rating Data,” *Journal of Infrastructure Systems*, 1995, 1(2), pp.120-125.

[Maybeck, 1979] Maybeck, P. S., *Stochastic Models, Estimation, and Control*, Vol.1, 1979, Academic Press, Inc.

[Mauch, 2001] Mauch, M. and S. Madanat, “Semiparametric Hazard Rate Models of Reinforced Concrete Bridge Deck Deterioration,” *Journal of Infrastructure Systems*, 2001, 7(2), pp.49-57.

[Meyer, 1987] Meyer, B. D., *Semiparametric Estimation of Duration Models*, Ph.D. Thesis, 1987, MIT, Cambridge, MA.

[Mishalani, 2002] Mishalani, R. G. and S. M. Madanat, “Computation of Infrastructure Transition Probabilities Using Stochastic Duration Models,” *Journal of Infrastructure Systems*, 2002, 8(4), pp. 139-148.

[Moavebzadeh, 1976] Moavebzadeh F., “Stochastic Model for Prediction of Pavement Performance,” *Transportation Research Record*, No. 575, 1976, pp.56-72.

[Nestorov, 1999] Nestorov, I., M. Rowland, S. T. Hadjitodorov, and I. Petrov, “Empirical Versus Mechanistic Modeling: Comparison of an Artificial Neural Network to a Mechanistically Based Model for Quantitative Structure Pharmacolunetic Relationships of a

Homologous Series of Barbiturates," *ASPS Pharmsic*, 1999, 1(4), pp.1-9.

[Okutani, 1984] Okutani, I. and Y. J. Stephanedes, "Dynamic Prediction of Traffic Volume through Kalman Filtering Theory," *Transportation Research Part B*, 1984, 18 (1), pp.1-11.

[Paterson, 1987] Paterson, W. D. O., *Road Deterioration and Maintenance Effects: Models for Planning and Management*, The International Bank for Reconstruction and Development, Washington, D.C., USA, 1987.

[Prozzi, 2001] Prozzi, J. M., *Modeling Pavement Performance by Combining Field and Experimental Data,* Dissertation, University of California at Berkley, 2001.

[Prozzi, 2000] Prozzi, J. A. and S. M. Madanat, "Using Duration Models to Analyze Experimental Pavement Failure Data," *Transportation Research Record*, No. 1699, 2000, pp.87-94.

[Small, 1987] Small, K. A., "A Discrete Choice Model for Ordered Alternatives," *Econometrica*, 1987, 55(2), pp.409-424.

[Small, 1988] Small, K. and C. Winston, "Optimal Highway Durability." *Academic Economic Review*, 1988, 78(3), pp.560-569.

[Sun, 2001] Sun, L., *Stochastic Performance Modeling Considering Maintenance Effects for Highway Pavement Management*, Dissertation, the University of Texas at Austin, 2001.

[TRB, 2005] Transportation Research Board (TRB), http://www.trb.org/mepdg/guide.htm, visited March 2005.

[UMTRI, 1998] University of Michigan Transportation Research Institute (UMTRI), http://www.umtri.umich.edu/erd/roughness/iri.html, visited October 2001.

[USDOT, 1999] USDOT and FHWA, Asset Management Premier, 1999.

[Welch, 2004] Welch, G. and G. Bishop, *An Introduction to the Kalman Filter*, http://www.cs.unc.edu/~welch/kalman/kalman_filter/kalman.html visited July, 2004.

[Wang, 1994] Wang, K. C. P., J. Zaniewski, and G. Way, "Probabilistic Behavior of Pavements," *Journal of Transportation Engineering*, 1994, 120(3), pp.358-374.

[West, 1997] West, M. and P. J. Harrison, *Bayesian Forecasting and Dynamic Models* (2nd Edition), Spring-Verlag: New York, 1997.

[Zhou, 2004] Zhou, X. and H. S. Mahmassani, "A Structural State Space Model for Real-Time Origin-Destination Demand Estimation and Prediction in a Day-to-Day Updating Framework," *Proceedings of 83rd Annual Meeting of the Transportation Research Board (CD-Rom)*, Transportation Research Board: Washington, D. C., 2004.

[Zimmerman, 2000] Zimmerman, K. A., F. Botelho, and D. Clark, *Taking Pavement*

Management into the Next Millennium, http://gulliver.trb.org/publications/millennium/00084.pdf, visited June 2000.

[Zhang, 1993] Zhang, Z., N. Singh, and W.R. Hudson, "Comprehensive Ranking Index for Flexible Pavement Using Fuzzy Sets Model," *Transportation Research Record*, No. 1397, 1993, pp.96-102.

VITA

Zheng Li was born in Zhoukou, Henan, China on October 26, 1977, the daughter of Yadong Li and Xinling Liu. After completing her study at Zhoukou No.3 High School in 1994, she entered Beijing University of Technology in Beijing, China. She received the degrees of Bachelor of Science, Master of Science from Beijing University of Technology in June 1998 and June 2001 respectively. Then, she entered the Graduate School of The University of Texas at Austin in August 2001. During her stay at the university, she worked as a graduate research assistant at the Center for Transportation Research of the University. She has presented and published several papers about her research. Her primary research interests include transportation infrastructure management, infrastructure performance evaluation and modeling, variability and reliability of infrastructures, and intelligent infrastructure systems.

Permanent Address: No. 4 Qiyilu Road, Building 3 Unit 2 Apartment 202

Henan, P. R. China 466000

This dissertation was typed by the author.